Estimates of Price Elasticities of Pharmaceutical Consumption for the Elderly

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Abstract

This paper estimates the price-elasticity of prescription drugs exploiting three unique features of the Spanish health system (1) the co-payment of prescription drug drops from 40% (10% for chronic diseases drugs) to 0% upon retirement, while the co-payment for the rest of health care services remains constant; (2) retirement jumps discontinuously at age 65, the legal retirement age, which allows us to use a Regression Discontinuity design to disentangle price from selection effects; and (3) absence of deductibles or caps in yearly or monthly out-of-pocket expenditure, which simplifies the computation of elasticities. We use administrative data from all individuals aged 63-67 covered by the National Health System in Catalonia (Spain) from 2004-2006. We find that the price-elasticity of prescription drugs is -0.20 for non-chronic condition drugs, and -0.08 or -0.03 for chronic conditions drugs. Given the size of our estimates, they remain informative even if we interpret them as being possibly biased away from zero (for reasons discussed in the paper). We also find a small increase in the expenditure on medically inappropriate drugs due to the decrease in co-payments.

Key words: Moral hazard, regression discontinuity analysis, medically inappropriate drugs.

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I. Introduction

How sensitive is health care consumption to changes in the price that individuals pay? The answer to this question has been at the cornerstone of the health economics literature since the late 60s (Pauly, 1968; Zeckhauser, 1970). Estimating the price elasticity of healthcare consumption was the main objective of the seminal RAND Health Insurance Experiment, and even the on-going Oregon Health Insurance Experiment specified the effect of insurance on health care use as its first hypothesis to test (Manning *et al.*, 1987; Newhouse, 1993; Finkelstein *et al.*, 2010 and Finkelstein *et al.*, 2012). Indeed, how much overconsumption is induced by insurance depends crucially on the price elasticity of health care consumption. Not surprisingly, the optimal co-payments are a function of the price-elasticity of each health care good (e.g. hospitalization; outpatient; inpatient) and each health care good possibly has a different price-elasticity (Besley, 1988).

In practice, the literature has focused on estimating the price-elasticity of total health care consumption, instead of a single health care good (see Zweifel and Manning, 2000; Cutler and Zeckhauser, 2000 and Cutler, 2002 for prominent reviews). Indeed, it is rarely the case that the co-payment of one type of health good changes while that of others remains constant, and complementarities or substitutability among different health care goods could bias the results if the prices of different health care goods change simultaneously.[1] In this paper, we exploit a unique feature of the Spanish health system in order to estimate the price-elasticity of pharmaceuticals: during our period of study the co-payment of prescription drug drops from 40% (10% for chronic diseases drugs) to 0% upon retirement, while the co-payment for the rest of health care services remains constant (at zero).[2] In addition, the fact that there are no deductibles or yearly out-of-pocket maximum (or "stop loss") facilitates the computation of the price-elasticities (as we do not have to deal with consumers' expectations of future

[1] Note that even in the RAND Health Insurance Experiment co-payment rates varied across individuals but not across types of health care services (Manning *et al.* 1987, and Newhouse 1993). An exception is Chiappori *et al.* (1998)

[2] A law approved in April 2012 (Royal Decree-Law 16/2012) increases the co-payments from July 2012 onwards.

expenditure).[3] These two features of the Spanish health system provide a framework which allows us to obtain a clean estimate of the price elasticity of prescription drugs.

The possibility of selection bias when estimating the response of health care consumption to price or coverage variations has been considered paramount in the literature (Cutler and Zeckhauser, 2000; Chiappori and Salanié, 2000; Einav and Finkelstein, 2011; Chetty and Finkelstein, 2012). In this paper, we disentangle price effects from selection effects (those going into retirement might be less healthy), by exploiting a jump in the probability of retirement that occurs at the legal retirement age (65 years). This allows us to apply a regression discontinuity (RD) design, which is highly regarded for its internal validity (Lee and Lemieux, 2010). Indeed, discontinuities in insurance coverage at specific ages have yielded robust estimates of the effect of health insurance on health care use and health outcomes (Card *et al,*. 2008; Card *et al.,* 2009; Shigeoka, 2011 and Anderson *et al.,* 2012). Closer to our main object of interest, Chandra *et al.* (2010) examined policy changes for Californian civil servants under Medicare program that increased the level of co-payment both for physician visits and prescription drugs. They provide one of the first robust estimations of price elasticity of pharmaceuticals for the elderly, as this group was excluded from the RAND Health Insurance Experiment.[4]

In this paper, we combine two different data sources to obtain the price-elasticity estimates. Administrative data on individuals aged 63-67 covered by the Catalonian Health Service during 2004-6 are used to estimate the change in prescription drugs consumption that takes place at age 65. For the same years, we use the Catalonian subsample of the Active Population Survey to estimate the change in the probability of retirement that takes place at age 65. By exploiting the discontinuity in the probability of retirement at age 65, we avoid comparing the drug consumption between retirees and non-retirees as ill health might trigger retirement rendering the two groups unlikely to be comparable (Dwyer and Mitchell, 1999; Disney *et al.*, 2006).

[3] See Keeler *et al*. (1977), Ellis (1986), Marsh (2011), and Aron-Dine *et. al* (2012).
[4] An important issue that we will not be able to consider is the possibility of offset effects (see Puig-Junoy *et al.*, 2011; Chandra *et al.*, 2010 and Gaynor *et al.*, 2006).

We find that the price-elasticity of prescription drugs for non-chronic conditions is -0.20. For most chronic conditions prescription drugs, the price elasticity is -0.08, while it is -0.03 for a particular subset of chronic condition drugs whose copayment is €2.64 (which represent less than 10%). These estimates are very similar across education groups. Our estimate of price-elasticity of drugs for non-chronic conditions (-0.20) is very similar to results from the RAND Health Insurance Experiment, as well as to recent estimates obtained by Chandra *et al.* (2010) for elderly Californian civil servants (-0.15).[5,6,7]

Comparing the elasticity of chronic and non-chronic drugs is both novel in the literature and informative from the point of view of designing insurance policies. Our result that chronic condition drugs are less price elastic than non-chronic drugs points in the direction that individuals should be better insured against chronic than non-chronic drug expenditure. Clearly, this is not a definitive conclusion, as there are other important factors that we cannot comment on: whether the probability of suffering one or another type of illness is under the individual's control (ex-ante moral hazard), the relative size of the lifetime financial loss for each type of drug, and the effects of each type of drug on health.

We decompose the increase in consumption which follows the co-payment drop into that driven by existing users and new users. We find that the latter is small in magnitude and hence most of the consumption increase comes from already users. This suggests that the higher pharmaceutical expenditure is not driven by the lower co-payments inducing more doctor visits.

[5] The RAND Health Insurance Experiment only enrolled individuals below 60 and hence most of their pharmaceutical consumption is likely to be non-chronic. We have been unable to find the price elasticities for drug consumption estimated using the RAND Health Insurance Experiment, but Leibowitz *et al.* (1985) report that the plan response for prescription medicines was similar to that of total outpatient care in the RAND Health Insurance Experiment.

[6] Chandra *et al.* (2010)'s estimate for HMO enrollees is -0.15, and -0.08 for PPO enrolees. Because provider choice is very limited in the Spanish health system, the comparison with HMO seems more relevant. They do not provide different results for non-chronic and chronic drugs. Given that we obtain -0.08 and -0.03 as price-elasticity estimates for chronic drugs, our estimate combining both non-chronic and chronic drugs should be close to -0.15.

[7] Puig-Junoy *et al.* (2011) also estimate price-elasticity estimates of prescription drugs but they only consider individuals who were already consumers before retirement. Their identification assumption differs from ours as they use the difference in drug consumption before and after retirement (after adjusting for fixed effects and time variant characteristics). Landsman *et al.* (2005) find price elasticity estimates from -0.16 to -0.10 for asymptomatic condition drugs and from -0.6 to -0.24 for symptomatic condition drugs. See Arcidiacono *et al.* (2012) for price elasticities of ulcer and reflux drugs.

According to the moral hazard hypothesis, overconsumption due to lower co-payments occurs because individuals consume health care goods whose individual's valuation is below the marginal social cost of producing them. An extreme consequence of this is when the health care goods are not medically appropriate. According to the "Beers criterion" (Beers *et al.,* 1991) 7.45% observations in our data correspond to medically inappropriate drugs. Interestingly, we find that the total quarterly expenditure on inappropriate drugs increases by €0.174 due to the decrease in the co-payment to 0%.

One could interpret our price-elasticity estimates as lower bounds if one suspected that the probability of visiting the doctor increased discontinuously at age 65, possibly because individuals who have just retired might experience a drop in the opportunity cost of time. This would bias our estimates away from zero. Even if that were the case, our estimates remain informative lower bounds because they are quite close to zero (especially in the case of drugs for chronic conditions). Though it is difficult to rule out completely, two pieces of evidence indicate that this is not an important bias in our context. First, we do not observe any change in the consumption of chronic drugs with the smallest pre-retirement co-payment (<10%). Second, our price-elasticity estimates are very similar across education groups but one would expect the opportunity cost of time to drop more for the most educated. Our explanation for this is that Spanish employment law provides generous allowance for doctor visits and work absences, and moreover those who are about to retire are unlikely to postpone doctor visits due to career pressures.[8]

An innovative aspect of this paper is to apply a regression discontinuity (RD) design in the case where the outcome and the treatment variable are drawn from different datasets. What is important for this application is that the variable that drives the discontinuity in treatment status (forcing variable) is available in both the dataset that contains the outcome variable and in the dataset that contains the treatment variable. This feature of the RD method is not well known - we are aware of no other papers that do this. However, it is potentially very useful in applied work.

[8] Although the Workers' Rights Act (*Estatuto de los Trabajadores*) does not regulate doctor visits explicitly, it allows the worker to be absent "for the minimum required time, to do one's personal or public duties" (art. 37). Besides, most collective bargaining agreements establish a generous allowance of paid hours to attend health related appointments.

Pharmaceutical spending accounts for a significant proportion of total health costs in developed countries. Mean expenditure on pharmaceuticals and other medical non-durables in OECD countries in 2009 amounted to 16.9% of total expenditure on health; 12% in the United States and 18.9% in Spain (OECD Health Data, 2011). Moreover, in Spain, public expenditure in pharmaceuticals was 1.3% of the GDP in 2007, one the highest rates in the EU. Spanish pensioners amount to 73.9% of pharmaceutical consumption in 2010, and this percentage has been increasing in the last decades (PortalFarma, 2012). Given the magnitude of drug consumption by the elderly, raising the co-payment rates of prescription drugs is among the policy options that Spanish policy makers have considered from time to time.[9]

The appropriate trade-off between inefficient drug consumption and risk spreading has also been of high importance in the US. Medicare Part D (an expansion of the public health insurance program, Medicare, to prescription drug-benefits) was passed in 2003 to provide insurance against drug expenditure risk to senior American citizens. Although the effect of this program on prescription drugs utilization is shown to be significant and positive (Lichtenberg and Sun, 2007; Yin *et al.*, 2008), some recent studies find evidence of heterogeneous effects. Zhang *et al.* (2009) show that there was an offsetting reduction in medical spending for those who had no or minimal drug coverage before the implementation of Part D. Engelhardt and Gruber (2011) found that there were substantial risk-reduction gains for those at the highest risk of spending, even though on average welfare gain on risk-reduction was comparable to the deadweight loss cost of financing the program.

The remainder of the paper is organized as follows. Section 2 briefly describes the institutional framework. Section 3 describes the datasets and provides a graphical analysis of the data. Section 4 describes the evaluation method, the identification and estimation strategy. Section 5 is devoted to the interpretation of the econometric results. Section 6 discusses the implications that several sources of bias have on our estimates. In Section 7 the main conclusions are summarized.

[9] Eventually, a new law was enacted in April 2012 which increased co-payments for prescription drugs for both retirees and non-retirees. We do not study this change because our data are only available until 2006.

II. Institutional Framework

In Spain, all legal residents are covered by the National Health Service (NHS) public insurance scheme which is mainly financed through general taxation. Individuals obtain access to health care in the NHS in a similar way as enrolees of a Health Maintenance Organization (HMO) in the US. Doctor visits, outpatient and inpatient treatment are free (zero co-payment) if obtained through the NHS network. If an individual seeks care outside of the NHS network, he must cover the full cost of the consultation/treatment.[10] For obvious reasons, non-NHS provided care represents a small percentage of total health care. For instance, amongst 63-67 years old, only 13% of doctor visits in the last fifteen days were to a non-NHS doctor.

Drugs are heavily subsidized if the prescription is written by an NHS doctor (on an NHS prescription form): Non-retired individuals pay 40% of the price of drugs for non-chronic conditions, and 10% for chronic condition drugs with a maximum of 2.64€ per prescription (this maximum only applies to chronic condition drugs). Crucially for our purpose, retired individuals pay zero for their prescription drugs. It is important to emphasize that both the retired and non-retired pay zero for doctor visits, outpatient and inpatient treatment if obtained through the NHS.

Individuals who seek care from an non-NHS provider can either (1) buy the drugs directly from the pharmacy using the non-NHS prescription and pay the full price of the drugs (hence forgoing the generous public subsidy mentioned in the paragraph above) or (2) visit an NHS doctor and ask him/her to re-write the non-NHS prescription as an NHS prescription which then would be entitled to the public subsidy.[11]

Regarding pension entitlements, Spain has a mandatory "pay as you go" system. In our period of analysis the legal age for retirement, although not mandatory, is 65 for both

[10] 15% of the population have private health insurance which will probably cover these costs. Individuals do not obtain any tax relief for buying private health insurance.
[11] Although NHS doctors are not obliged to do so, it is common knowledge that the vast majority do.

men and women.[12] Earlier retirement is penalized through a decrease in pension benefits. Later retirement increases pension benefits only for those who had contributed at least 35 years.[13]

III. Data and graphical analysis

Our RD empirical strategy requires that we observe prescribed drug expenditure and labour force status: active or retired, but not necessarily in the same dataset. We combine different sources of data to access all the necessary information.

III.1 Pharmaceutical consumption

We combine the administrative pharmaceutical consumption record from the Catalonian NHS with the Central Register of Insured Individuals (*RCA-Registre Central d'Assegurats*) to obtain data from all individuals covered by the Catalonian NHS who were between 60-64 years-old on 31/12/2003 (n=281,589). We follow these individuals three years until 31/12/2006. This data is also combined with the "Nomenclator DIGITALIS-INTEGRA" database from the Spanish Ministry of Health to obtain information on the characteristics of the prescribed drugs. Our database only contains drugs acquired using an NHS prescription form (see section II). In section VI, we consider in detail the possible implications of this for our estimates. In the worst possible scenario, it might imply that our estimates are biased away from zero (although given how close they are to zero, they remain quite informative).

We use the following three variables to measure pharmaceutical consumption: total expenditure (the sum of the retail prices of all prescribed drugs bought), number of prescriptions, and "Defined Daily Dose" (DDD).[14] We present our estimates using all three measures although we highlight our results using total expenditure as this is the most common measure used in the literature (results on number of prescriptions and

[12] In July 2011 Spanish parliament passed Law 27/2011 (*Ley sobre Adecuación, Adaptación y Modernización del Sistema de Seguridad Social*) that modifies retirement age. This law becomes effective in 2013 and extends gradually legal retirement age up to 67 years old.
[13] Law 35/2002 which was active between July 2002 and January 2008.
[14] DDD is an international accepted classification system for drug consumption. World Health Organization defines DDD as "the assumed average maintenance dose per day for a drug used for its main indication in adults" (http://www.whocc.no/atcddd/).

DDDs can be found in the Appendix A). We show results separately for non-chronic condition drugs subject to 40% co-payment for the non-retired, chronic condition drugs subject to 10% co-payment for the non-retired, and chronic condition drugs subject to an out-of pocket payment of €2.64 per prescription. As indicated above, retired individuals pay 0% for all drugs (receive 100% subsidy).[15]

For each individual, prescribed drug consumption measures are aggregated at the quarter level. This not only follows Card *et al.* (2008, 2009), but also coincides with the minimum window available for the employment data that we will review below. Moreover, in practice, retirees need a special card to pay zero for the prescription drugs. This card can take anything between 4 and 8 weeks to receive; so many individuals who are 65 years and one month would not yet be paying zero. This is why we will not consider the first three months after 65 in the analysis. The selection of the bandwidth is determined by the availability of data as we only observe individuals up to 67 years old.

The descriptive statistics for key variables of interest of our final dataset are listed in Table 1. The data we use contain 2,019,826 observations on 281,589 individuals. The mean age of our sample is 64.5 and 51% of the observations relate to women. Regarding education level, 15.7% have achieved high school or college diploma. In almost 50% of the observations there is positive consumption. Regarding drug quarterly consumption: average total expenditure is €70.1, average out of pocket expenditure is 2.73 €, average number of prescriptions is 5, and average number of DDDs is 121.9.

Figure 1 shows drug total expenditure (actual and fitted) on non-chronic conditions drugs by each age quarter from age 63 to 67. In particular, the dots are the residuals of a regression of the dependent variable (drug total expenditure) on time dummies (month in which the drug was consumed).[16] The lines are regression fits, from a linear model that allows for a different first order age polynomial on either side of the cut-off point (65 years of age). Figure 2 (3) shows the same graph but for chronic condition drugs with a pre-retirement co-payment of 10% (less than 10%: €2.64 per prescription).

[15] 22% of the chronic drugs prescriptions are subject to the €2.64 maximum.
[16] We condition on the month of consumption because pharmaceutical consumption might be seasonal and the average age in the sample is not uniformly distributed across the months in the sample.

Figures 1-3 show that drug total expenditure increases linearly with age, and that the slopes are extremely similar on either side of age 65. While there is clear evidence of a discontinuity in non-chronic drug total expenditure at age 65 (Figure 1), it is either much smaller or non-existent for chronic drug expenditure (Figure 2 and Figure 3).

III.2 Retirement status

Data on retirement status is obtained using the Active Population Survey (*Encuesta de Población Activa*). This is a quarterly cross-section nationally representative survey, routinely used to estimate the unemployment rate. We use the Catalonian subsample for the 12 quarters that cover our period of analysis (2004-2006). Our key variable is whether the individual is retired or not, as retired individuals do not pay anything for prescription drugs.

The third column of Table 1 lists the descriptive statistics for key variables of the Active Population Survey: our sample contains 7,174 observations, 64.1% of whom are retired. Comparing the second and third column of Table 1, it is clear that the sample of the two datasets (drug consumption dataset and Active Population Survey) are very similar.

As mentioned above, the legal age for retirement, although not mandatory, is 65 for both men and women (earlier retirement is penalized through a decrease in the drawn benefit, postponement of retirement increases pension payout only for those who had contributed at least 35 years). Figure 4 shows the proportion of retired individuals by each age quarter from 63 to 67. The solid dots are the average proportion of retirees at each quarter of age. The lines are regression fits, from a linear model that allows for a different first order age polynomial on either side of the cut-off point (65 years of age). The discontinuity at age 65 suggests that legal incentives have a powerful effect on the retirement decision.

IV. Empirical Strategy

A key issue in estimating the price elasticity of prescription drugs is how much of the change in pharmaceutical consumption that happens upon retirement is due to the drop in co-payment rates (from 40% or 10% or less to 0%), and not due to health shocks that

trigger retirement. To isolate the effect of co-payment changes, we use a Regression Discontinuity design and exploit the sharp increase in retirement rates that occurs at 65 years, the legal retirement age. The crucial identification assumption is that there are no other discontinuities at age 65 in variables that affect drug consumption except for the discontinuity in the co-payment rate.[17,18] In section VI, we consider possible threats to the basic identification assumption.

Because not all individuals retire at age 65, we use a fuzzy regression discontinuity design (Hahn *et al.*, 2001).[19] If E[ ] denotes the expectation operator, *C* denotes a measure of pharmaceutical consumption, *R* denotes a binary variable that takes value 1 if the individual is retired and 0 otherwise, and *a* denotes age, then the ratio

$$\frac{\lim_{a\to 65^{+}} E[C \mid a] - \lim_{a\to 65^{-}} E[C \mid a]}{\lim_{a\to 65^{+}} E[R \mid a] - \lim_{a\to 65^{-}} E[R \mid a]} \qquad (1)$$

identifies the causal effect of the co-payment changes associated with retirement on pharmaceutical consumption for the compliers (those individuals who retire because they have reached the legal retirement age).[20]

Defining B_{it}=**1[b>=0]** as a binary variable that takes value 1 if the individual *i* is older than 65 years at time *t* and 0 if younger, ratio (1) can usually be estimated using B_{it} as instrument for R_{it} in the regression below

$$C_{it} = g(a_{it}) + R_{it}\pi + m_t + \varepsilon_{it} \qquad (2)$$

[17] This is similar to Card *et al.* (2008) and (2009) who rely on the only discontinuity at age 65 being in insurance coverage.

[18] In most RD designs, a second condition must be added that individuals cannot completely manipulate the forcing variable. In our case, manipulation is not a possibility because our forcing variable is age. This is reported to the social security system at the beginning of the individual's working life, and it must match the national identity card records. A birth certificate is required when issuing the national identity card.

[19] Early applications of the Regression Discontinuity method included Thistlethwaite and Campbell (1960), Angrist and Lavy (1999), Black (1999) and Van der Klaauw (2002). Imbens and Lemieux (2008), and Lee and Lemieux (2010) provide up to date surveys on RD methods.

[20] See Hahn *et al.* (2001); Imbens and Angrist (1994)

where $g(\ )$ is a smooth polynomial function of a_{it}, m_t denotes month fixed effects, and ε_{it} an error term. The estimate of treatment effect, ratio (1), is given by the estimate of the parameter π. However, we cannot estimate regression (2) because R_{it} and C_{it} are not available in the same dataset. Consequently, our estimation strategy is based on estimating the numerator and the denominator of (1) separately, each with a different dataset. In particular, we use OLS to estimate both:

$$C_{it} = g(a_{it}) + B_{it}\pi_n + m_t + v_{it} \tag{3}$$

and

$$R_{it} = g(a_{it}) + B_{it}\pi_d + m_t + u_{it}. \tag{4}$$

Regressions (3) and (4) are estimated using the administrative pharmaceutical consumption records from the Catalonian NHS and the Active Population Survey respectively.[21] We exclude from the estimation the quarter that starts with 65 years because, as already explained, the card required to be eligible for the 0% co-payment can take one or two months to be issued. Given the clear linear pattern with constant slope that emerges from Figures 1, 2, 3 and 4, we choose a linear first order polynomial in a_{it} for the function $g(\ )$. The estimate of the treatment effect, ratio (1), is given by the ratio of the estimates of π_n and π_d, in particular:

$$\hat{TE} = \left(\frac{\hat{\pi}_n}{\hat{\pi}_d} \right) \tag{5}$$

We take into account the following features of the data when estimating the standard errors of $\hat{\pi}_n$, $\hat{\pi}_d$ and $\hat{TE}$. First, the forcing variable, age, is discrete and consequently the regression is prone to specification error which can be taken into account by clustering the standard errors by age (Lee and Card, 2008). Second, the administrative drug consumption record from the Catalonian NHS is longitudinal and there are several observations for the same individual. Consequently, we also cluster the standard errors at the individual level to consider the correlation of errors for the same individual over

[21] Due to data limitations, we use quarter rather than month fixed effects in equation (4).

time. Third, the number of clusters as defined by age is relatively small, 17, and standard statistical formulae for clustered standard errors based on asymptotic theory (cluster-correlated Huber-White estimator) have been shown to provide standard error estimates that are too small if the number of clusters (age bins here) is small (Donald and Lang, 2007; Wooldrige, 2004; Bertrand *et al.,* 2004 and Cameron *et al.,* 2008).[22] We use wild bootstrap-se standard errors as they are conservative according to Cameron *et al.* (2008). Moreover, we use the formulae provided by Miller *et al.* (2009) to take into account the two-way clustering (age in quarters and individuals) when using the administrative drug consumption data from the Catalonian NHS. [23]

V. Results

V.1 Main Results

Table 2 presents estimates of reaching age 65 on the probability of going into retirement (π_d in regression 4). As suggested in Figure 4, the probability of going into retirement increases sharply upon reaching age 65. Our results indicate that reaching 65 increases the probability of being retired by 10 percentage points. The impact is very similar across high educated (12 percentage points) and low educated (10 percentage points).

Table 3 presents estimates for the impact of going into retirement at age 65 on drug total expenditure (*TE* in 5).[24] We find that total quarterly expenditure on non-chronic drugs increases by €15.41. Consistent with Figures 2 and 3, the increase for chronic drugs is much smaller (less than €2) and not statistically significant for those drugs for which out-of-pocket payment is capped at €2.64 per prescription (co-payment <10%). Interestingly, the increase is very similar for the low and high educated.

Table 4 shows the estimates of the arc price-elasticity of drug total expenditure. The price elasticity for non-chronic conditions drugs is -0.20, while it is -0.08 for chronic condition drugs (-0.03 for chronic condition drugs with an out-of-pocket payment

[22] Cameron *et al.* (2008) indicate 30 as a rule of thumb for when the number of clusters can be considered small, but they indicate that in general it will depend on the level of intra-cluster correlation and the number of observations per cluster.
[23] See Appendix C for more details on the computation of standard errors.
[24] Tables A1 and A2 in Appendix A show the results for the number of drug prescriptions and DDDs respectively.

capped at €2.64). It is expected that chronic condition drugs are more inelastic as they must be taken regularly due to the nature of the diseases they are prescribed for. Tables A3 and A4 in Appendix A report very similar price elasticities for the quantities of drugs as for expenditure (independently of whether quantities are measured as number of prescriptions or DDDs).

The price elasticity of expenditure is a crucial term in the formula to compute the optimal co-payment (Besley 1988).[25] The result that chronic conditions drugs are less price elastic point in the direction that co-payments for chronic drugs should be smaller. However, it must be acknowledged that several other factors could reverse this recommendation: larger externalities or health effects of non-chronic drugs, larger financial losses due to non-chronic drugs, and more scope for ex-ante moral hazard in chronic drugs.[26]

V.2 New or existing users

We estimate the increase in the probability of consuming any drug due to retirement at age 65 by estimating (5) but using as dependent variable in equation (3) whether or not the individual consumed any drugs in the quarter. The results are reported in Table 5. We find that the proportion of new consumers changes very little, especially that of consumers of drugs for chronic conditions (0.01 or 0.007).

The estimates of Table 5 are useful to address how much of the increase in the consumption is due to new consumers and how much comes from existing consumers. We obtain this by separating our RD estimate into two effects: first, the increase in total expenditure which is due to new users (which is calculated by multiplying the corresponding increase reported in Table 5 by the estimated total expenditure at age 65.25 for those retired), and second, the increase in total expenditure which is due to existing users.

[25] Elasticities play a crucial role in the determination of optimal benefits in different types of social insurance models (see Chetty and Finkelstein 2012 for a recent review).
[26] Lower co-payment for chronic drugs could decrease the incentives for individuals to invest in healthy lifestyles and hence increase the probability of suffering some chronic diseases (i.e. diabetes).

For non-chronic condition drugs, we find that only 12.4% of the increase in the drug total expenditure is explained by new consumers. For chronic condition drugs for which the 10% co-payment rate applies, we find that only 5.8% of the total increase is due to new users. For those chronic condition drugs where co-payment rate is less than 10%, we find an increase of 10%, but not statistically significant. These findings support the hypothesis that most of the increase in total expenditure is due to existing users, rather than new users.

V.3 Appropriate use

In order to learn more about the behavioural response of the change in health insurance coverage, we carry out the analysis distinguishing the drugs according to their appropriateness. For this purpose we apply the "Beers criterion" (Beers *et al.*, 1991) updated by Fick *et al.* (2003) to our dataset. This is the most predominant explicit classification of the quality of the prescription for the elderly and has been widely applied in the literature (see, for instance, Gallagher *et al.*, 2008; Costa-Font *et al.*, 2010). Their criteria are based on consensus by experts in geriatric care in the US and they define inappropriate medications as those which entail more potential risks than benefits.

Applying this criterion we identify 31 inappropriate active principles in our sample, which represents 7.45% of all observations. We find that total quarterly expenditure on inappropriate medications increases by €0.174. This is statistically significant at the 10% level.[27] We then analyse how the proportion of new consumers of inappropriate medication changes using the procedure explained in the previous subsection. We find that the proportion of new consumers changes 0.009 which means that only 6.9% of the total increase in the drug total expenditure on inappropriate medications is due to new users. These results are reported in Table 6.

[27] Regarding inappropriate medication, we also find that doses increase by 0.383 (bootstrapped standard error 0.2238) and prescriptions by 0.011 (0.0275).This last standard error is the maximum of the standard errors obtained from one-way clustering along each possible dimension as the resulting variance when implementing the two-way formula was negative.

VI. Biased away from zero?

In this section we discuss two possible sources of bias in our estimates: (1) doctor visits could discontinuously increase at age 65 and (2) our dataset only contains information on drugs prescribed by NHS doctors. As we argue below, if these biases were important, they would bias our estimates *away* from zero. Below, we provide suggestive evidence that these biases are unlikely to be quantitatively important in our case. However, it is important to highlight that our estimates remain informative even if these biases are present, because our elasticity estimates are already reasonably close to zero (especially the chronic drug ones), so our estimates could be interpreted as informative upper bounds (in absolute value).[28]

Total doctor visits (irrespective of whether they are to an NHS or non-NHS provider) could increase abruptly post-retirement because the individual faces a lower opportunity cost of time.[29] More doctor visits might translate into more drug prescriptions. In that case, we would be overestimating the change in consumption and thus our elasticity measures would be biased away from zero. We do not believe this to be of first order importance because health concerns are likely to dominate career ones for those close to retirement, so workers would be more inclined to take time off to visit the doctor. Moreover, as we indicated above, the Spanish law is quite generous with permissions to go the doctor.

A second source of bias comes from visits to non-NHS doctors, which are around 13% of total visits for individuals aged 63-67. Individuals who visit a non-NHS doctor and obtain a prescription from him/her can either (1) buy the drugs directly from the pharmacy and pay the full price of the drugs (hence forgoing the public subsidy of 60% or 90% if the individual is not retired and 100% if the individual is retired) or (2) visit an NHS doctor and ask him/her to re-write the prescription issued by the non-NHS doctor on an NHS prescription form which then would be eligible for the public subsidy. One concern is that the proportion of individuals who behave according to (2)

[28] A different concern would be if hypothetical changes in income due to retirement could affect pharmaceutical consumption. We do not think that this is an issue given that co-payment rate is 0 after retirement.

[29] It is theoretically possible that doctor visits decrease post-retirement if individuals' health improves (i.e. individuals have more time to allocate to health improving activities). However, it is unlikely that health improves much in the six month period (64.75 to 65.25) from which we identify the effect.

increases discontinuously upon retirement at the expense of individuals following (1). This is important because the drugs purchased using prescriptions from non-NHS doctors, those in (1), are not recorded in our dataset. This effect would also bias our elasticity estimates away from zero. We do not think that this is an important issue because we believe that most individuals will follow (2) even pre-retirement, given that the public subsidy on prescription drugs is already quite large (60%, 90% or even more) and the visit to the NHS doctor is free.

In both of the cases above, we would be overestimating the change in consumption upon retirement and thus our elasticity measures would be biased away from zero. In this case, we can still interpret our elasticity estimates as upper bounds (in absolute value). Note that our estimates are already reasonably small, so they are quite informative even as upper bounds.

Whether these two possible sources of bias are important or not is an empirical issue. We cannot provide conclusive evidence, but several results of our analysis alleviate concerns about them. First, even for those drugs with the lowest pre-retirement co-payment (less than 10% of the price of the prescription), the last column of Table 3 (as well as Figure 3) showed evidence of no discontinuity in total drug expenditure. Second, one would expect these sources of bias to be more important for the high educated (whose opportunity cost of time is higher while working, and who are more likely to visit a non-NHS doctor), yet we find that the price elasticities are very similar for high and low educated which suggests that doctor visits do not increase discontinuously at 65. Third, according to our results in Table 5, most of the increase in total drug expenditure comes from individuals who were existing users, rather than for those who became new users post-retirement. Hence, it is unlikely that our individuals are starting to visit the NHS doctor upon retirement.

VII. Conclusions

Estimating the price-elasticity of a single type of health care goods has remained challenging because co-payments for different goods often change simultaneously and hence complementarities or substitutions among health care health care goods might bias findings. In this paper, we estimate the price elasticity of prescription drugs for the elderly by exploiting several unique features of the Spanish Health System. First, co-payments for prescription drugs fall from 40%, 10% or less to 0% upon retirement, which itself increases discontinuously at 65 years old, the normal retirement age in Spain. Second, co-payments to other health services (medical consultations, outpatient and inpatient treatment) remain constant. Third, there is no deductible or maximum out-of-pocket expenditure (monthly, yearly, etc) which usually complicates the computation of the price elasticities.

We find that the price-elasticity of prescription drugs for non-chronic conditions is -0.20. For chronic conditions prescription drugs, the price elasticity is -0.08 (-0.03) for those whose pre-retirement co-payment is 10% (less than 10%). Our price-elasticity estimates are very similar to those obtained for other types of care and populations. One could interpret our results as upper bound estimates (in absolute value) because of a possible abrupt increase in doctor visits following retirement and because we do not observe drugs purchased using non-NHS doctor prescriptions. However, several pieces of evidence suggest that these are unlikely to be a major source of bias. Even as upper bounds, we consider our elasticity estimates to be quite informative because they are reasonably small.

One limitation is worth highlighting. The design we apply allows us to measure the elasticity on pharmaceutical consumption on a short-term basis only. Whilst this is a limitation, at the same time it ensures that the effects we are measuring are not affected by the consequences that retirement could have on health which may occur over a longer period of time.

These findings have implications for the design of an optimal co-payment scheme for prescriptions for the elderly. They also provide important information to policy makers

as they allow for the accurate prediction of the expected budgetary impacts of changes to co-payment rates for prescription drugs.

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Tables and figures

Table 1. Descriptive statistics for key variables

	Drug consumption database	Active population survey
Age (mean)	64.5	65
Female	51%	51.60%
High Educated (high school and college)	15.70%	18.70%
Retired		64.10%
Bought any prescribed drugs	49.8%	
Expenditure (euros, mean)	70.1	
Out of pocket expenditure (euros, mean)	2.73	
Defined Daily Doses* (mean)	121.9	
Prescriptions (mean	5	
n (# individuals)	281,589	7,174
N (# observations)	2,019,826	7,174

*Restricted to 1,500 DDD per quarter.

Table 2. Changes in the probability of going into retirement at age 65

All	0.100***
	[0.0084]
Low educated	0.096***
	[0.0126]
High educated	0.123***
	[0.0377]

Note: Each entry shows the estimate of πd (regression 4) for different samples (defined by education). The regression includes age, post-65 dummy and quarter fixed effects. Standard errors (in brackets) are calculated using a wild bootstrap-se by age. *** Denotes significance at the 1% level.

Table 3. Regression Discontinuity Estimates (total drug expenditure in euros)

ALL		
Non-chronic	**Chronic (10%)**	**Chronic (<10%)**
15.41***	1.93***	1.39***
[2.7393]	[0.3072]	[2.6531]
{40.03}	*{11.48}*	*{19.84}*
LOW EDUCATED		
Non-chronic	**Chronic (10%)**	**Chronic (<10%)**
15.55***	1.65***	-1.27
[2.7043]	[0.2884]	[3.2470]
{41.97}	*{12.01}*	*{20.34}*
HIGH EDUCATED		
Non-chronic	**Chronic (10%)**	**Chronic (<10%)**
13.62***	1.32**	3.29
[4.5105]	[0.5545]	[2.3770]
{36.48}	*{10.82}*	*{18.28}*

Note: Each cell shows the estimate of *TE* (equation 5) for a different sample (as defined by type of drug and individual's education).The regression includes age, post-65 dummy and time fixed effects. Standard errors (in square brackets) are calculated applying a wild bootstrap-se procedure accounting for multi-way cluster structure. The estimated mean post-65 total drug expenditure for retired individuals is in curly brackets. *** Denotes significance at the 1% level, ** 5% level.

Table 4. Estimates of arc price-elasticity of total drug expenditure

ALL		
Non-chronic	**Chronic (10%)**	**Chronic (<10%)**
-0.20***	-0.08***	-0.03
[0.0360]	[0.0141]	[0.0648]
LOW EDUCATED		
Non-chronic	**Chronic (10%)**	**Chronic (<10%)**
-0.19***	-0.07***	0.03
[0.0310]	[0.0119]	[0.0760]
HIGH EDUCATED		
Non-chronic	**Chronic (10%)**	**Chronic (<10%)**
-0.20***	-0.06**	-0.09
[0.0678]	[0.0294]	[0.0677]

Note: Each column shows the estimates of the arc price-elasticity, according to the type of drug and individual's education. The measure of drug consumption is indicated in the title of the table. Standard errors (in square brackets) are calculated applying a wild bootstrap-se procedure accounting for multi-way cluster structure. *** Denotes significance at the 1 % level, ** 5 % level

Table 5. Changes in the proportion of consumers

Non-chronic	Chronic (10%)	Chronic (<10%)
0.048***	0.010***	0.007
[0.018]	[0.004]	[0.007]

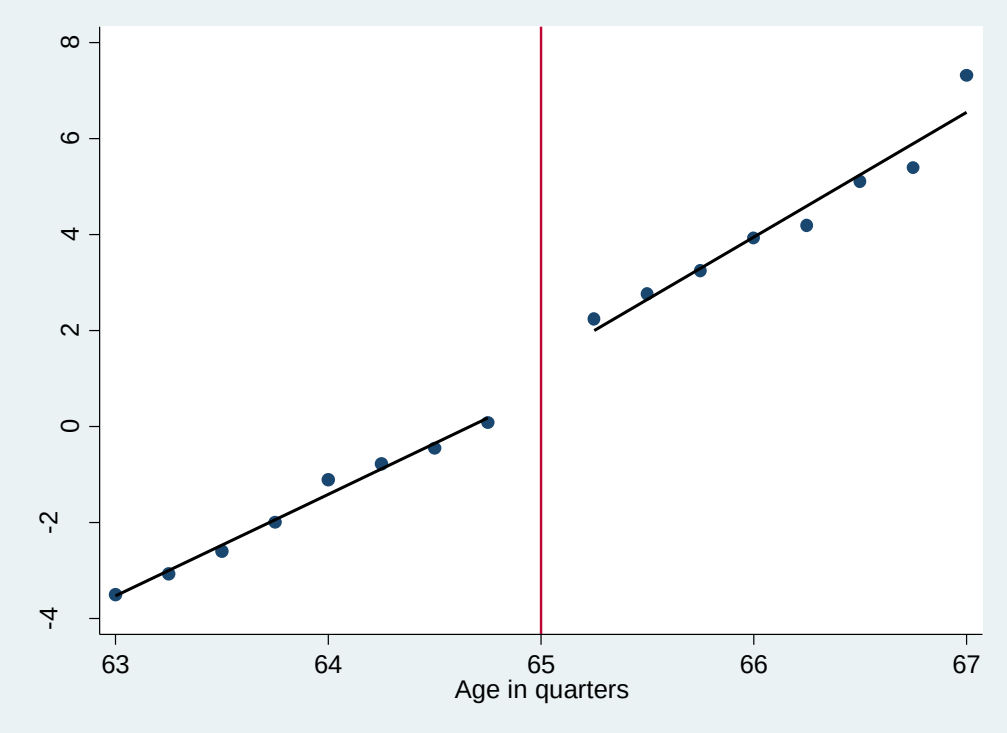
Note: Each column shows coefficients for a different regression, according to the type of drug. Entries are regression discontinuity estimates from models that include age, post-65 dummy and time fixed effects. The dependent variable is a dummy variable indicating whether or not the individual consumed any drug in the quarter. Standard errors (in square brackets) are calculated applying a wild bootstrap-se procedure accounting for multi-way cluster structure. *** Denotes significance at the 1% level.

Table 6. Changes in the inappropriate use

Expenditure	New users
0.17*	0.01***
[0.1031]	[0.002]

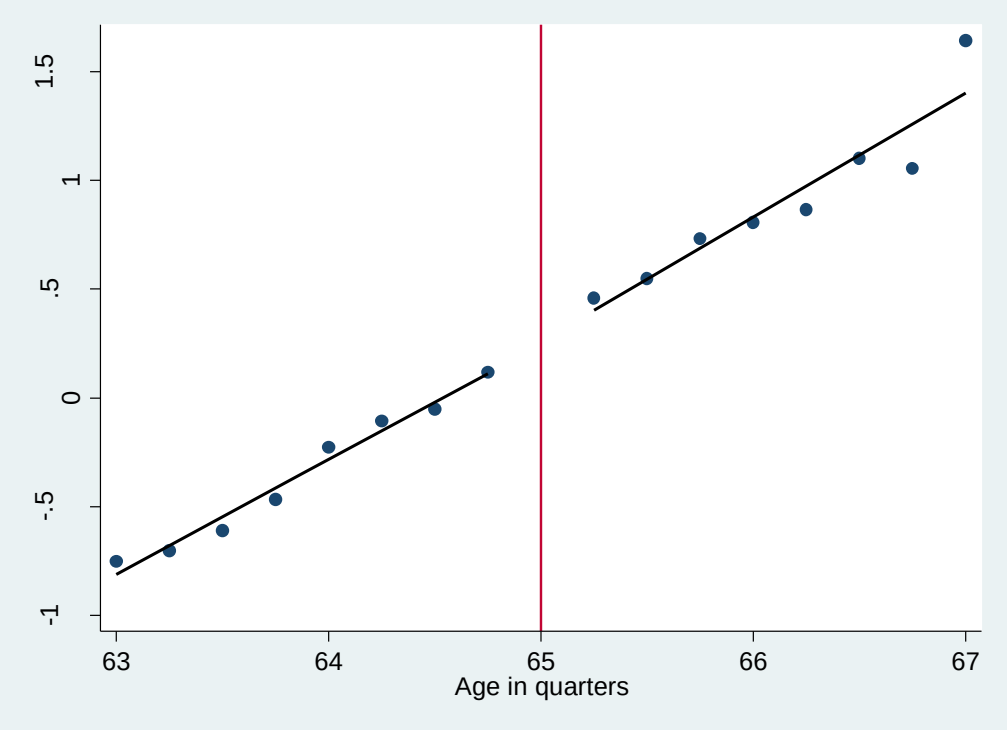
Note: Entries are regression discontinuity estimates from models that include age, post-65 dummy and time fixed effects. In the first column the dependent variable is total drug expenditure on inappropriate medication. In the second column the dependent variable is a dummy variable indicating whether or not the individual consumed any inappropriate drug in the quarter. Standard errors (in square brackets) are calculated applying a wild bootstrap-se procedure accounting for multi-way cluster structure. *** Denotes significance at the 1 % level, * 10 % level.

Figure 1. Total drug expenditure on non-chronic condition drugs by age.



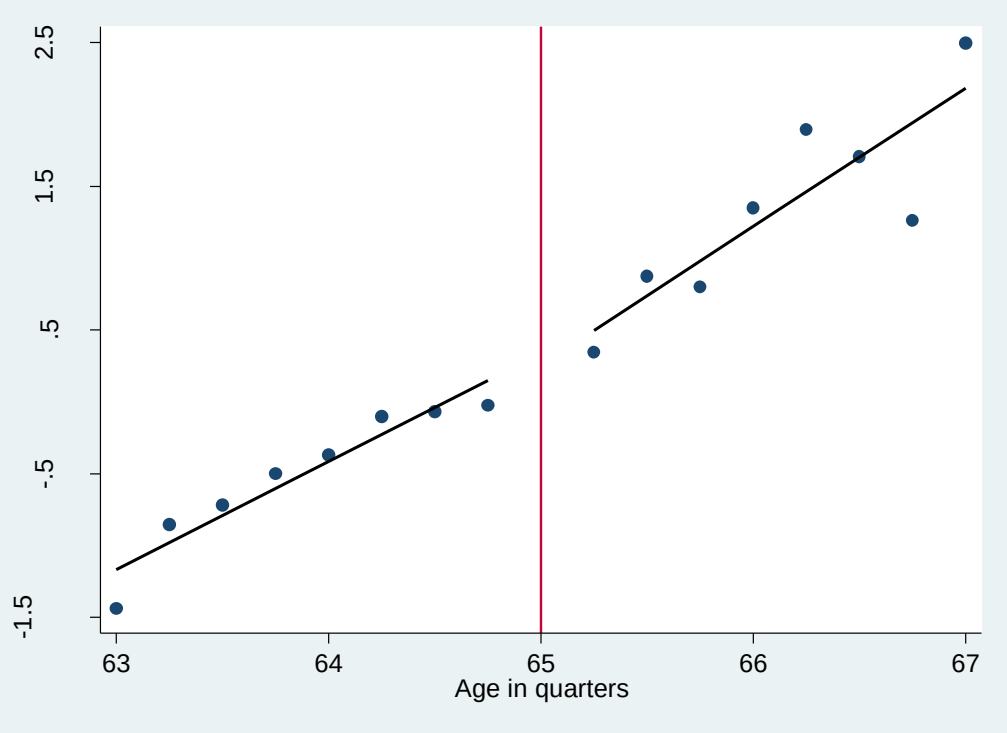
Note: The dots are the average of the residuals of a regression of drug expenditure (euros) on month dummies, i.e. month in which the drug was consumed. The lines are regression fits, from a linear model that allows for a different first order polynomial in age on either side of 65.

Figure 2. Total drug consumption on chronic condition drugs (10% co-payment) by age.



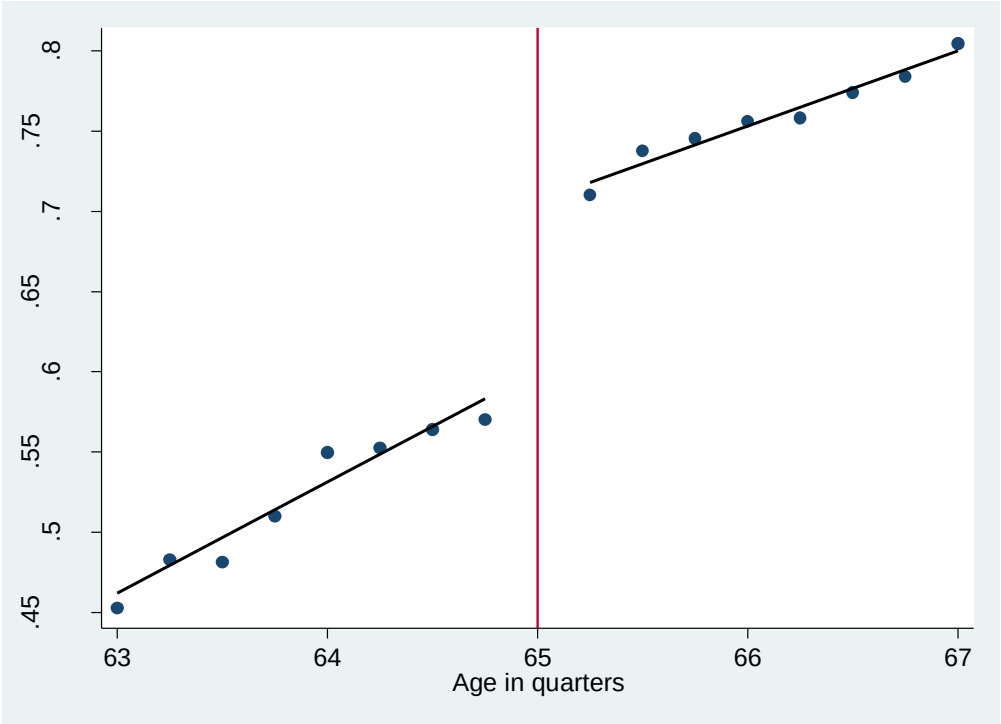
Note: The dots are the average of the residuals of a regression of drug expenditure (euros) on month dummies, i.e. month in which the drug was consumed. The lines are regression fits, from a linear model that allows for a different first order polynomial in age on either side of 65.

Figure 3. Total drug expenditure on chronic condition drugs (< 10% co-payment) by age.



Note: The dots are the average of the residuals of a regression of drug expenditure (euros) on month dummies, i.e. month in which the drug was consumed. The lines are regression fits, from a linear model that allows for a different first order polynomial in age on either side of 65.

Figure 4. Proportion of retirees by age.



Note: The dots are the average proportion of retirees at each quarter of age. The lines are regression fits, from a linear model of retired status on age, a dummy variable that indicating 65 or older, an interaction term between age and dummy variable for being older than 65 and a time variable that indicates the quarter in which the survey was conducted.

APPENDIX A:

Additional Tables

Table A1. Regression Discontinuity Estimates (number of prescriptions)

ALL		
Non-chronic	**Chronic (10%)**	**Chronic (<10%)**
1.28***	0.23***	0.04
[0.27]	[0.06]	[0.03]
{3.44}	*{1.32}*	*{0.35}*
LOW EDUCATED		
Non-chronic	**Chronic (10%)**	**Chronic (<10%)**
1.24***	0.17***	0.02
[0.25]	[0.06]	[0.03]
{3.63}	*{1.36}*	*{0.37}*
HIGH EDUCATED		
Non-chronic	**Chronic (10%)**	**Chronic (<10%)**
1.25**	0.26**	0.02
[0.56]	[0.14]	[0.04]
{2.86}	*{1.15}*	*{0.29}*

Note: Each cell shows the estimate of *TE* (equation 5) for a different sample (as defined by type of drug and individual's education). The regression includes age, post-65 dummy and time fixed effects. Standard errors (in square brackets) are calculated applying a wild bootstrap-se procedure accounting for multi-way cluster structure. The estimated mean post-65 number of prescriptions for retired individuals is in curly brackets. *** Denotes significance at the 1% level, ** 5% level.

Table A2. Regression Discontinuity Estimates (DDDs)

ALL		
Non-chronic	**Chronic (10%)**	**Chronic (<10%)**
25.72***	8.78***	1.55
[5.51]	[1.41]	[1.51]
{75.03}	*{44.53}*	*{13.55}*
LOW EDUCATED		
Non-chronic	**Chronic (10%)**	**Chronic (<10%)**
24.43***	6.68	0.24
[5.05]	[4.61$^{\text{Y}}$]	[1.51]
{78.59}	*{46.72}*	*{14.03}*
HIGH EDUCATED		
Non-chronic	**Chronic (10%)**	**Chronic (<10%)**
22.62***	11.78***	0.76
[11.05]	[4.25]	[1.37]
{64.79}	*{39.83}*	*{11.04}*

Note: Each cell shows the estimate of *TE* (equation 5) for a different sample (as defined by type of drug and individual's education). The regression includes age, post-65 dummy and time fixed effects. DDDs (Defined Daily Doses) are restricted to 1,500 per quarter. Standard errors (in square brackets) are calculated applying a wild bootstrap-se procedure accounting for multi-way cluster structure. The estimated mean post-65 drug consumption (DDDs) for retired individuals is in curly brackets. *** Denotes significance at the 1% level. $^{\text{Y}}$ denotes the maximum of the standard errors obtained from one-way clustering along each possible dimension as the resulting variance when implementing the two-way formula was negative.

Table A3. Estimates of arc price-elasticity of the number of prescriptions

ALL		
Non-chronic	**Chronic (10%)**	**Chronic (<10%)**
-0.19***	-0.09***	-0.05
[0.04]	[0.02]	[0.04]
LOW EDUCATED		
Non-chronic	**Chronic (10%)**	**Chronic (<10%)**
-0.17***	-0.06***	-0.03
[0.04]	[0.02]	[0.03]
HIGH EDUCATED		
Non-chronic	**Chronic (10%)**	**Chronic (<10%)**
-0.24**	-0.12*	-0.04
[0.11]	[0.07]	[0.06]

Note: Each column shows the estimates of the arc price-elasticity, according to the type of drug and individual's education. The measure of drug consumption is indicated in the title of the table. Standard errors (in square brackets) are calculated applying a wild bootstrap-se procedure accounting for multi-way cluster structure. *** Denotes significance at the 1 percent level, ** 5 % level, * 10 % level.

Table A4. Estimates of arc price-elasticity of drug consumption (DDDs)

ALL		
Non-chronic	**Chronic (10%)**	**Chronic (<10%)**
-0.18***	-0.10***	-0.05
[0.04]	[0.02]	[0.05]
LOW EDUCATED		
Non-chronic	**Chronic (10%)**	**Chronic (<10%)**
-0.16***	-0.08***	-0.01
[0.03]	[0.004]	[0.05]
HIGH EDUCATED		
Non-chronic	**Chronic (10%)**	**Chronic (<10%)**
-0.19**	-0.17***	-0.03
[0.09]	[0.06]	[0.06]

Note: Each column shows the estimates of the arc price-elasticity, according to the type of drug and individual's education. The measure of drug consumption is indicated in the title of the table. DDDs (Defined Daily Doses) are restricted to 1,500 per quarter. Standard errors (in square brackets) are calculated applying a wild bootstrap-se procedure accounting for multi-way cluster structure. *** Denotes significance at the 1 % level, ** 5 %level.

APPENDIX B

Appendix B

In this Appendix, we provide details on the computation of the elasticities that we report in the paper. We estimate the arc price-elasticity of the demand of pharmaceuticals ($\hat{E}_p$) using the following expression:

$$\hat{E}_p = \frac{\frac{\Delta C}{(C_1 + C_2)/2}}{\frac{\Delta P}{(P_1 + P_2)/2}}$$

where ΔC is our $T\hat{E}$ (the regression discontinuity estimate, see (5)); P_1 is the pre-retirement price, C_1 is the quantity (measured either as total cost, DDDs or number of prescriptions) purchased at P_1, P_2 is the post-retirement price and C_2 is the quantity purchased at P_2. $\Delta P = P_2 - P_1$. The values of P_1, P_2, and ΔP follow the table below:

	Non-chronic drugs	Chronic drugs	Chronic drugs (priced capped)
P_1	0.4P	0.1P	2.64
P_2	0	0	0
ΔP	-0.4P	-0.1P	-2.64

As we indicated in the article, we do not observe who is retired or not in the dataset in which we observe C. Hence, we cannot directly measure either C_1 or C_2. To tackle this, we solve the following system of equations:

$$\begin{aligned} C^{65^-} &= R^{65^-} \times C_2^{65^-} + (1 - R^{65^-}) \times C_1^{65^-} \\ C^{65^+} &= R^{65^+} \times C_2^{65^+} + (1 - R^{65^+}) \times C_1^{65^+} \\ C_2^{65^+} &= C_2^{65^-} + (2 \times \theta_a) \\ C_1^{65^+} &= C_1^{65^-} + (2 \times \theta_a), \end{aligned}$$

where C^{65^-} and C^{65^+} are C at ages 64.75 and 65.25 respectively, R^{65^-} and R^{65^+} are the proportion of retired individuals at ages 64.75 and 65.25 respectively, $C_1^{65^-}$ and $C_1^{65^+}$ are the levels of C for non-retired individuals at ages 64.75 and 65.25 respectively, $C_2^{65^-}$ and $C_2^{65^+}$ are the levels of C for retired individuals at ages 64.75 and 65.25 respectively, and θ_a is the age coefficient in equation (3).[30] Note that $\left(C_1^{65^-}, C_1^{65^+}, C_2^{65^-}, C_2^{65^+}\right)$ is the vector of unknowns but the other parameters can be either directly estimated from the data (C^{65^-},C^{65^+},R^{65^-}, R^{65^+}) or taken from the estimates of our econometric models (θ_a).

After solving for $\left(C_1^{65^-}, C_1^{65^+}, C_2^{65^-}, C_2^{65^+}\right)$ in the system of equations above, we use

$$\begin{aligned} C_1 &= (1 - R^{65^-}) \times C_1^{65^-} + (1 - R^{65^+}) \times C_1^{65^+} \\ C_2 &= R^{65^-} \times C_2^{65^-} + R^{65^+} \times C_2^{65^+}, \end{aligned}$$

[30] Note that we multiply by 2 the age coefficient because we are evaluating the change from 64.75 to 65.25, and not from 64.75 to 65.

to obtain $C_1$and C_2, and be able to compute the elasticity using the formulae above.

As we report elasticities for each type of drug, we apply this procedure separately for each type of drug (non-chronic, chronic, chronic but with price capped) and for each quantity indicator (total drug expenditure, DDDs, and number of prescriptions).

APPENDIX C

Appendix C

We consider the following features of the data when computing the standard errors of our estimates: (1) the forcing variable, age, is discrete which calls for clustering at the level of age (Lee and Card, 2008), (2) the number of age cluster is relatively small, 17, and hence the standard errors need to be bootstrapped, (3) the drug consumption dataset is longitudinal and hence errors of the same individual are correlated over time which calls for clustering at the individual level. (1) and (3) together imply that we need to correct for two-way clustering. Following Cameron *et al.* (2011), the variance of $T\hat{E}$ corrected for two-way clustering is:

$$\mathbf{V}(T\hat{E})= \mathbf{V^A}(T\hat{E})+ \mathbf{V^I}(T\hat{E})- \mathbf{V^U}(T\hat{E}), \qquad \text{(C.1)}$$

where $\mathbf{V^A}$ is the variance adjusted for clustering by age, $\mathbf{V^I}$ is the variance adjusted for clustering by individual, and $\mathbf{V^U}$ is the variance assuming independence across observations, that is, without cluster adjustment. We compute $\mathbf{V^A}$, $\mathbf{V^I}$, and $\mathbf{V^U}$, by drawing bootstrap samples at the appropriate cluster level (age, individual, or without cluster adjustment). Because the number of clusters as defined by age is relatively small, we draw the samples using wild bootstrap instead of the more standard pair bootstrap. Wild bootstrap has shown to provide conservative standard errors when the number of clusters is small (Cameron *et al.*, 2008). Note that $T\hat{E}$ is a ratio ($T\hat{E} = \left(\frac{\hat{\pi}_n}{\hat{\pi}_d}\right)$) and its variance across the 1,000 pseudo-bootstrap samples can "explode" if the value of the denominator is very close to zero even in one pseudo-bootstrap sample. To avoid this problem, we use a robust estimator of the standard error of $T\hat{E}$, based on the assumption of normality. In particular, we estimate the standard error of $T\hat{E}$ as:

$$\mathbf{SE}(T\hat{E}) = \frac{P_{75}-P_{25}}{2*0.6745}, \qquad \text{(C.2)}$$

where P_{75} and P_{25} are the 75th and 25th percentiles of $T\hat{E}$ across the 1,000 pseudo-bootstrap samples.[31] This provides an estimate of the standard error of $T\hat{E}$ which is robust to values of the denominator very close to zero for some pseudo-bootstrap sample.[32]

We obtain similar results when we use the Delta Method, which does not require using (C.2). To use the Delta Method, we need the standard errors of the numerator, $\hat{\pi}_n$, and the denominator, $\hat{\pi}_d$. For the latter, we use wild bootstrap clustering by age to take into account that the number of clusters (when defined by age) in the Active Population Survey is relatively small. The standard error of the numerator is estimated using

$$\mathbf{V}(\hat{\pi}_n)= \mathbf{V^A}(\hat{\pi}_n)+ \mathbf{V^I}(\hat{\pi}_n)- \mathbf{V^U}(\hat{\pi}_n), \qquad \text{(C.3)}$$

[31] Under the Normality assumption, $\frac{P_{75}-E(TE)}{SE(TE)}$=0.6745 and $\frac{P_{25}-E(TE)}{SE(TE)}$= - 0.6745. After substracting one to the other, one obtains $\mathbf{SE}(T\hat{E}) = \frac{P_{75}-P_{25}}{2*0.6745}$.

[32] The results are not sensitive to the percentiles used. We obtain similar results if we use $\mathbf{SE}(T\hat{E}) = \frac{P_{97.5}-P_{2.5}}{2*1.96}$.

because we consider clustering at both age (as in the case of the Active Population Survey) and individual level when using the pharmaceutical consumption dataset.[33] We use the standard White-estimator to estimate $\mathbf{V^U}(\hat{\pi}_n)$, and the standard cluster adjusted Huber-White estimator to estimate $\mathbf{V^I}(\hat{\pi}_n)$ because the number of individual based clusters is large. As the number of age based clusters is relatively small, we use wild bootstrap to estimate $\mathbf{V^A}(\hat{\pi}_n)$. Once we have estimated $\mathbf{V^A}(\hat{\pi}_n)$, $\mathbf{V^I}(\hat{\pi}_n)$ and $\mathbf{V^U}(\hat{\pi}_n)$, we can apply (C.3) and obtain an estimate of the standard error of $\hat{\pi}_n$, which is used together with the standard error of $\hat{\pi}_d$ and the Delta Method to obtain the standard error of $T\hat{E}$.

[33] Unlike the Active Population Survey, the pharmaceutical consumption dataset is a panel and hence clustering at the individual level must be taken into account.