Medicare Part D: Are Insurers Gaming the Low Income Subsidy Design?

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Abstract

In Medicare Part D, low income individuals receive a subsidy for enrollment into insurance plans. This paper studies how premiums are distorted by the combined effects of this subsidy and the default assignment of low income enrollees into plans. Removing this distortion could reduce the cost of the program without worsening consumer welfare. Using data from the the first five years of the program, instrumental variable estimates indicate a positive effect of this distortion on the premium growth, especially for the premium component directly paid by Medicare.

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1 Introduction

Medicare Part D is the voluntary program offering Medicare enrollees insurance for prescription drugs. It is organized as a market in which private insurance companies compete to offer diverse insurance plans to Medicare enrollees under the rules established by the Medicare legislation. In 2011, around 26 million people were enrolled in Medicare D plans and the program cost was $55 billion to the government.

In addition to being economically relevant by itself, Medicare D is also the only example of public insurance delivered exclusively through a choice-based private insurance market. Thus, studying Medicare D helps with assessing the potential merits of one of the main models of healthcare reform currently debated. Not surprisingly, opposite positions have emerged in the policy debate with advocates of the program stressing that its cost is substantially less than expected, while opponents point to its very steep increase in costs in recent years. Indeed, despite the cost for the government remaining essentially the same for the first three years, about $40 billion per year from 2006 to 2008, the cost increased by about 11% per year in the following three years, reaching $55 billion in 2011, see Table 1.

Academic research on Medicare D suggests that three distinct elements are needed for Medicare D to work properly: consumers must be able to select insurance plans effectively, plans must steer consumption toward generics and less expensive drugs and, finally, plans must compete to maintain low premiums. Most of the existing studies have focused on the first issue, typically finding that many consumers make mistakes in choosing plans, but that their choices improve as they gain more experience. As regards the second issue, Duggan and Scott Morton (2010, 2011) have found that plans designed their drug formularies in ways that very effectively increased drugs substitutability and limited drug cost increases. The third pillar of Medicare D, competition between plans, however, has received substantially less attention, with the only exception being the study of Ericson (2010) on pricing responses to consumers' inertia in plan choice.

In this paper, I contribute to the analysis of insurer competition in Medicare D by showing how the design of the public subsidies has distorted firm pricing behavior. About 90% of plan revenues do not come from enrollees payments but from various Medicare subsidies. Therefore, the way in which these subsidies are set is of crucial importance in understanding plans prices. In turn, these prices are what determines the increases in the costs of the program observed in recent years and, ultimately, the efficiency of the system.

The major source of distortion that I identify is the so called Low Income Subsidy (LIS) that Medicare pays to enrollees of limited financial resources. About 9 million enrollees (40% of all enrollees) are entitled to this subsidy, which is a major source of plan revenues. In 2011, the LIS accounted for $22.3 billion of the $61.5 billion paid to plans, making the LIS the single most important source of plans revenues.[1] The basic idea for why this subsidy affects insurers behavior is straightforward if four facts are simultaneously considered: First, about ⅔ of the 9 million LIS enrollees do not actively select an insurance plan. They are allocated by the Center for Medicare and Medicaid Services (CMS) to plans with a premium not greater than the LIS itself. Conditional on an insurer having at least one plan with its premium at or below the subsidy, the allocation rule keeps the LIS enrollees within the same insurer from year to year and, otherwise allocates them at random across the insurers offering plans with premiums at or below the subsidy. Second, CMS pays in full premiums for LIS enrollees. Third, the amount of the subsidy is an average of plans premiums. Fourth, all major insurers offer multiple plans that enter into the calculation of the subsidy.

At the most basic level, this means that a firm offering multiple plans can maintain just one plan with a premium equal to the low income subsidy and set high premiums for all its other plans to inflate the subsidy. The large number of LIS enrollees and the fact that they do not require either marketing expenses or a quality above the minimum needed to qualify for Medicare D suggests that firms will respond to this incentive. Like in an auction, the LIS enrollees are treated by the regulation as a "prize" given to plans pricing below a certain threshold. However, this threshold is endogenously determined by plan premiums and can be manipulated. Moreover, this distortion also affects the non-LIS enrollees both because the plans among which they choose also serve LIS enrollees and because each plan must charge the same premium to all its enrollees, regardless of their LIS receiver status.

[1] Table 1 reports the various sources of payments to plans, which are explained in detail in the Section 2.

This distortion is closely connected with that observed in two other cases recently at the center of attention: the LIBOR rate and the average bid auctions. The latter is a reference interest rate used to set payments on about $800 trillion-worth of financial instruments. This rate is set daily by asking 16 large banks to state the rate at which they are willing to borrow money and then calculating the average of the 8 middle rates. In the summer 2012, it became public that some banks were coordinating their reported rates in order to make bets on LIBOR changes that were highly likely to be successful. As of February 2013, Barclays had settled with the regulators for a fine of US$450 million and UBS for a record fine of US$1.5 billion, with charges to other ten banks expected to follow. Similarly, in the average bid auctions (ABAs), often used to procure public works, the winner is the firm offering the price closest to the average of the offered prices. In several countries where ABAs are used, collusion was discovered with coalitions of firms coordinating on how to pilot the average price (Conley and Decarolis, 2013). An important difference between these cases and Medicare D, however, is that in Medicare D insurers have multiple plans and, hence, subsidy manipulation does not require collusion, but results automatically from individual firm profit maximization. Indeed, the various types of subsidy manipulation that I describe in this paper are not collusion and it is by no means clear whether they represent a violation of any existing regulation.

This study aims to quantify how economically relevant is the premium distortion arising from the insurers' response to the LIS regulations. To empirically quantify this effect, I analyze data on plan enrollment and prices between 2006 and 2011. In particular, I focus on how the growth in the average premium in the 34 geographical regions into which the US is divided can be explained by differences in the manipulability of the LIS. Since the LIS is a weighted average of plan premiums, the measure of manipulability used is simply the sum of the four highest weights in a region. The analysis necessitates using an instrumental variable approach because the linkage between the weights used to compute the LIS and the changes in the premium would mechanically produce downward biased OLS estimates.

The main findings of the analysis reveal a clear association between LIS manipulability and premium growth. In particular, the preferred specification indicates an increase of 8.7%

in premium growth in response to a one standard deviation increase in the concentration of the weights used to determine the LIS. This estimate is robust to the use of different model specifications and to different sets of instruments. It implies that of the 36% nominal growth of basic premiums observed between 2006 and 2011, about 58% can be explained by the growth in the concentration of the weights used for the low income subsidy calculation observed in the same period. In a second set of results, I look separately at the component of the premium that is paid directly by Medicare and at the one that is paid by non-LIS enrollees. These findings reveal that the effect of the LIS manipulation affects predominantly the premium paid by Medicare, thus confirming that the LIS distortion is a relevant cause of the increase in the program cost for Medicare. Finally, in a third set of results, I describe various patterns in the data taken at the level of the individual plans which broadly confirm the distortionary effect of the LIS on premiums.

These findings help answer two puzzles posed by the literature. First, despite Hsu et al. (2010) showing that Medicare is not sufficiently risk adjusting the payment made to plans for their LIS enrollees, insurers have systematically shown a preference for retaining their LIS enrollees whenever given the option to do so.[2] Second, a recent study by Duggan and Scott Morton (2011) analyzed whether premium growth could be explained by the price and utilization of brand name drugs. Their conclusion was that premium growth could not be explained by that factor and that the source of the increase was still an open question. The findings in this paper offer a single answer to these two puzzles by showing that the manipulability of the LIS subsidy both makes the LIS enrollees particularly valuable despite their insufficient risk adjustment and has a large impact on the observed premium growth.

The main policy implication of this paper is to deliver evidence in support of a drastic reform of the low income subsidy in Medicare D. This system has been the object of strong concerns especially after a 2011 study by the Office of the Inspector General found that the unitary costs of 200 commonly purchased drugs were substantially higher under Medicare D than under Medicaid. Since the vast majority of LIS enrollees are *dual eligibles* of Medicare

[2]For instance, a rule known as *de minimis policy* provides the opportunity to retain LIS enrollees if plans agree to offer a discount to these enrollees. As described later, the discount varies across plans but it can be in the order of almost 10% of the monthly premium. Nevertheless, the 58 plans that faced this choice in 2011 all decided to apply the discount.

and Medicaid, their return to a system similar to Medicaid has been proposed. Alternatively, the allocation of these enrollees to specially designed plans, not available for regular enrollees has also been debated. Although this study does not assess which of these two proposals is preferable, it can help identify the problems of less drastic solutions that would not separate the markets of LIS and non-LIS enrollees. For instance, forcing insurers to have no more than one plan eligible for LIS enrollees without addressing the issue of the endogenous determination of this subsidy would most likely end in the replication of what was seen in the cases of the LIBOR and the ABAs.

Related literature

This paper contributes to the studies of the Medicare Part D program, which is extensively described in Duggan, Healy and Scott Morton (2008). The most direct contribution of this research is to offer a novel explanation for the increased program cost. Duggan and Scott Morton (2010, 2011) argue that this increase is not driven by changes in drug costs. A similar conclusion is reached by Aaron and Frakt (2012). Ericson (2010), instead, offers an explanation of the cost increases based on firms exploiting consumers inertia in plan choice. My analysis is complementary to that of Ericson (2010).

Secondly, this paper contributes to the studies of Medicare D efficacy and efficiency. Most of the existing studies have focused on consumers' choice of plans. Several of them have concluded that choices are suboptimal (Heiss, McFadden and Winter, 2007, Abaluck and Gruber, 2009, and Kling, Mullainathan, Shafir, Vermeulen and Wrobel, 2010, Heiss, Leive, McFadden and Winter, 2012). However, Ketcham, Lucarelli, Miravete and Roebuck (2012) have argued that over time consumers rapidly improve their choice of plan. This paper, by arguing that prices are distorted, suggests that prices cannot properly guide consumers choices. Thus, efficiency in this market requires solving not only the consumers difficulties in making choices but also firm pricing distortions. Moreover, the paper shows how plan proliferation is, at least in part, due to the LIS distortion. Reforming the LIS would likely simplify the choice problem of non-LIS enrollees by reducing the number of plans offered.

Furthermore, the population of LIS enrollees that I study is of great policy interest. The LIS enrollees are mostly Medicare/Medicaid dual eligibles, whose high drug consumption is particularly costly. The system through which Medicaid provides drugs has been extensively studied. Its key element is a mandatory rebate that drug manufacturers have to offer to Medicaid. Because of this rebate, the Office of General Inspector (2011) has concluded that drug costs are lower under Medicaid than under Medicare D. Frank and Newhouse (2008) had already suggested this possibility and proposed a return to prices closer to those in Medicaid. They do not suggest a return to Medicaid because, as shown in Scott Morton (1997) and Duggan and Scott Morton (2006), the mandatory rebate induces drug manufactures to distort prices for non-Medicaid enrollees. This paper contributes to this literature both by describing how Medicare D LIS regulation distorts plan premiums for all enrollees and by suggesting elements of a possible reform.

Finally, this paper contributes to a recent wave of studies asking whether a market mechanism could deliver efficient outcomes in complex and heavily regulated health insurance markets. In particular, Glazer and McGuire (2009) and Bundorf, Levin and Mahoney (2012) show how the requirement of a uniform price across consumers distorts prices and allocations. Medicare D also requires a uniform price and, hence, it is possibly subject to this problem. This study, however, focuses on a different source of distortions: The design of public subsidies. Given the use of a similar design in other health care markets, the results will be relevant for these other markets. For instance, similar mechanisms are used in Medicare Part C and in the Medicare DEMPOS (Durable Medical Equipment, Prosthetics/Orthotics & Supplies) auctions studied by Katzman and McGeary (2008) and Cramton et al. (2011). At the most general level, all these studies confirm the intuition from the principal-agent literature on multitasking (Holmstrom and Milgrom, 1991) that designing a market to achieve certain desiderata is hard whenever these desiderata contrast with firms profitability and firms can take multiple actions. Duggan and Scott Morton (2006) discuss other examples of this related to health care markets.

The rest of this paper is organized as follows: Section 2 presents a theoretical example, Section 3 describes the market regulations, Section 4 presents the data, Section 5 illustrates the empirical strategy, Section 6 reports the empirical findings and, finally, Section 6 concludes.

2 Theoretical Example

Suppose there are 3 firms, each one offers one insurance plan. Consumers are divided into two groups: Unsubsidized enrollees at the beginning of each period choose one plan and pay its premium. Subsidized enrollees, instead, at the beginning of each period are assigned by Medicare to a plan, but they pay no premium. Switching between plans can occur only at the beginning of a period. Indicating the three plans as q, j and k, the cost of enrolling a consumer is c_r^U if the consumer is unsubsidized and c_r^L if he is subsidized, for $r \in \{q, j, k\}$.

The regulations require that all consumers in the same plan r pay the same premium, p_r, for $r \in \{q, j, k\}$. Therefore, in any period t the profits of the firm offering plan r is:

$$\Pi_{r,t} = [p_{r,t} - c_{r,t}^U] s_{r,t}^U M^U + [p_{r,t} - c_{r,t}^L] s_{r,t}^L M^L \quad \text{for } r \in \{q, j, k\}.$$

Where M^U and M^L are the total number of unsubsidized and subsidized consumers and $s_{r,t}^U$ and $s_{r,t}^L$ their shares in plan r in period t. These two shares depend on the premiums. For $s_{r,t}^U$, as usual in discrete choice models of differentiated product industries, we can assume that the indirect utility of an unsubsidized consumer i for plan r is: $u_{i,r} = \delta_r - \alpha p_r + \epsilon_{i,r}$ where δ_r is the plan quality, fixed for each plan. If $\epsilon_{i,r}$, the idiosyncratic preference of i for r, is distributed as Type I Extreme Value, this gives rise to the usual logit formula for $s_{r,t}^U$.

The share s_r^L behaves very differently. Medicare assigns subsidized consumers to plans based solely on their premium. First a weighted average of plans premiums, $LIPSA_t = \sum_{r \in \{q,j,k\}} w_{r,t} p_{r,t}$, is computed using weights that are positive and sum to one.[3] Then, subsidized enrollees are allocated to plans with a premium smaller or equal to $LIPSA_t$. Thus, $p_{r,t} > LIPSA_t$ implies that plan r cannot enroll subsidized enrollees in t. If such plan had subsidized enrollees in $t-1$, they are reassigned in equal shares to plans with $p_t \leq LIPSA_t$. These latter plans also maintain in t any subsidized enrollee that they had in $t-1$.

Clearly, which weights are used to compute $LIPSA_t$ can greatly influence the evolution of

[3]Throughout the rest of the paper, I use LIPSA to indicate the amount of the subsidy (often with regard to a specific region and year). Meanwhile, I use LIS to refer to the more general notion of this subsidy. Thus, whenever I refer to the weights used to calculated the subsidy, they are addressed as LIPSA weights.

market shares. In particular, if weights are previous period enrollment shares of subsidized enrollees, a system I refer to as “enrollment weighting”, then over time there will be a tendency for all subsidized enrollees to converge into a single plan. To see why, suppose that there is an initial period, $t = 1$, in which $w_{q,1} = w_{j,1} = w_{k,1} = 1/3$. From $t = 2$ onward, enrollment weighting is used. Suppose that premiums are ordered as $p_q < p_j < p_k$ and are fixed over time. Then, certainly $p_k > LIPSA_1$ and possibly also $p_j > LIPSA_1$. In the second period either $LIPSA_2 = p_q$ or $LIPSA_2 = (.5)p_q + (.5)p_j$. In both cases $p_j > LIPSA_2$ and so in at most two periods all subsidized enrollees are in plan q. When prices are set in equilibrium, they may or may not stay constant through time. This can alter the speed of the process, but as long as there is no continuous reshuffling of which is the cheapest plan(s), convergence into the cheapest plan(s) will happen. On the contrary, no such tendency exists in an ”equal weighting” system in which all premiums are always weighted equally.

Under enrollment weighting, a firm that, due to its unfavorable cost conditions, cannot offer a cheap plan will eventually loose all its subsidized enrollees. However, before then, this firm might try to keep its premium within LIPSA for as many periods as possible if doing so ensures high enough profits on subsidized enrollees, even though charging an higher premium would have been optimal considering only unsubsidized enrollees.[4] Since over time enrollment weighting increases the weights of the cheapest plans, it might cause a competitive pressure toward low premiums. In contrast, no such pressure exists under equal weighting.

Nevertheless, both weighting schemes are problematic when insurers offer more than one plan, as insurers in Medicare D typically do. To illustrate this, I consider again an environment with three plans: q, j, k, but now assuming that the market is a duopoly with plans j and k belonging to the same multiplan firm. A relevant change to the rule for the assignment of subsidized enrollees is that when at time t a plan of the multiplan firm that enrolled subsidized consumers in $t-1$ has a premium above $LIPSA_t$, then all the subsidized enrollees it had in $t-1$ are reassigned to the other plan of the multiplan firms in period t, provided that this plan has a premium at or below $LIPSA_t$. Hence, the multiplan firm loses all its subsidized enrollees only if in the same period both $p_{j,t} > LIPSA_t$ and $p_{q,t} > LIPSA_t$.

[4] On the contrary, a firm finding subsidized enrollees too costly might rise its premium above LIPSA.

The following numerical example shows why this can generate perverse effects. Suppose that an unsubsidized consumer i has utility for plan r: $u_{i,r} = \delta_r - p_r$ for $r = q, j, k$ and receives a utility of zero from not enrolling. Assume that $\delta_q = 1 > 0.1 = \delta_j = \delta_k$, so that, if all premiums were the same, all unsubsidized consumers would prefer the high quality plan q. Despite being high quality, q has also the lowest cost: $c_j = c_k = 1 > .01 = c_q$. Finally, there is a regulation stating that no premium can be higher than a ceiling price of 4.[5]

Under enrollment weighting, the only pure strategy Nash equilibria of this duopoly game lasting T periods are those of the type illustrated (for the first three periods) in Figure 1. In the first period, the premiums are $p_q = 1$, $p_j = 2.5$ and $p_k = 4$ and, because they are equally weighted, the $LIPSA_1$ equals 2.5. All the unsubsidized consumers choose plan q. The subsidized enrollees are assigned half to plan q and for half to plan j. In the second period, the prices are $p_q = 1$, $p_j = 4$ and $p_k = 2.5$. Thus $LIPSA_2$ equals again 2.5. Plan q maintains all its subsidized enrollees. Instead, all the subsidized enrollees that were in plan j are moved to plan k. In all the following periods, j and k continue endlessly their alternation: The plan that had positive enrollment of subsidized enrollees in $t-1$ chooses a premium of 4 in t, which keeps the LIPSA as high as possible. The other premium is then set equal to the LIPSA at 2.5, which is the highest price that the multiplan firm can charge without losing all the subsidized enrollees. Since plan q is already charging the highest premium to retain the unsubsidized enrollees, it has no incentive to interfere with j and k if the relative size of subsidized over total enrollees is sufficiently small. Under equal weighting, the strategy profile just described is also an equilibrium, but keeping constant the premiums at $p_q = 1$, $p_j = 4$ and $p_k = 2.5$ is an equilibrium too.

This stylized example shows a number of unpleasant features of the system when there is a multiplan firm. Profit maximization will lead this firm to use its plans to extract the highest rents from the system. In the example above, Medicare pays forever 2.5 for half of the subsidized enrollees while it could have paid 1. Moreover, five other problems arise. First, production is inefficient because half of the subsidized consumers remain forever

[5]The presence of a known ceiling price is a simplification that captures the idea that CMS can ask firms to revise premiums when it judges them to be unreasonably high. I also assume a floor price of 1 to rule out equilibria where the multiplan firm earns negative profits in the first period to earn larger profits afterwards.

in plans with the highest cost. Second, subsidized consumers are excessively reassigned, cycling forever between plans j and k. This might imply changes in drug formularies that require consumers to change drugs. Third, it is unfair for subsidized consumers because for purely random reasons half of them get forever high quality and the others low quality. Fourth, paradoxically the inefficient multiplan firm earns an higher profit per enrollee than the efficient firm. The efficient firm would like to enter with an additional plan to mimic the multiplan firm. Inefficient entry might thus be another distortion induced by this system. Fifth, the role of the ceiling price is essential as it avoids that the premiums explode. In practice, Medicare does not announce such price but it achieves something similar by having the right to assess premiums reasonableness and to ask for revisions accordingly. Performing such a process is a delicate and costly activity.[6]

To conclude this Section, it is useful to discuss how in practice a multiplan firm could exploit the enrollment weighting system. Indeed, since Medicare supervises the market, it is unlikely that it will tolerate a cycling of premiums and enrollment like the one in the example. Nevertheless, insurers in Part D have more refined strategies to achieve the same result. For instance, at the beginning of each period a firm can consolidate any old plan into either an existing plan or a new plan. In 2010, CIGNA achieved through plans consolidation something remarkably similar to what is done by the multiplan firm in the example. For Medicare D, the US territory is divided into 34 distinct geographical regions. The strategy that I now describe was used by CIGNA in 14 of them. To make this description concrete, I focus on region 20 (Mississippi). In 2009 CIGNA had only one plan[7] in this region and 96% its enrollees were subsidized (13,737 out of 14,310). In 2010, two new plans, one "cheap" ($28.1 premium) and one "expensive" ($34.1), were introduced and the old plan was consolidated into the *expensive* plan. This meant that CIGNA consolidation choice maximized its positive influence on the subsidy (i.e., the LIPSA): Its expensive plan had a weight of 8% (inherited from the consolidated plan), while its cheap plan had a weight of 0%. Once the LIPSA was calculated, the premium of the expensive plan resulted to be above the LIPSA and so

[6]Finally, competition between multiplan firms does not necessarily help. For instance, adding a second multiplan firm, identical to the fist, leaves all the negative features of the example unchanged.

[7]Throught this example about CIGNA with the term "plan" I am actually meaning "basic plan." The next section explains what basic plans are.

this plan lost its subsidized enrollees. But none of them were lost for CIGNA itself because they were reassigned to its cheap plan. Had CIGNA consolidated the old plan directly into the cheap plan, rather than forcing a Medicare mandated reassignment, the LIPSA would have been 2% lower (holding all other premiums fixed). CIGNA applied this same strategy in other 13 regions that year. Overall, 60,846 subsidized enrollees had to be moved out of CIGNA plans because of Medicare mandated reassignment due excessively high premiums, but the company reabsorbed all of them through other, cheaper plans. The discussion of other related strategies follows the description of the market regulation.

3 Market Regulation

The regulation of Medicare Part D is complex and has changed over time. The aim of this section is to offer a quick overview of the program in terms of the types of plans and enrollees as well as to describe the system of subsidies. Special attention is given to the calculation of the low income subsidy and the assignment of low income enrollees to plans.

The program divides the US territory into 34 geographical regions. For each region, firms submit in June to CMS the list of plans that they commit to offer the following year. CMS then verifies that plans conform to regulatory requirements in terms of their financial structure (premium, initial deductible, coinsurance/copayment for the various drugs) and formulary (the list of covered drugs). It is useful to consider two distinctions between plans. The first one is between plans covering only Medicare approved drugs (basic plans) and those covering also additional drugs outside the Medicare list (enhanced plans).[8] The premium of enhanced plans is divided into two components, basic and enhanced, and Medicare subsidies can be used only to pay for the basic portion. The second distinction between plans is whether they offer only Medicare Part D services (i.e., discounts on certain drugs), in which case they are known as Prescription Drug Plans (PDPs), or whether they also offer Medicare Part C (i.e., the benefits of traditional Medicare A and B), in which case they are known as Medicare Advantage Prescription Drug plans (MA-PDs). The list of approved plans is then

[8]Basic plans can be further subdivided into three distinct groups that differ in their coverage structure. See Duggan et al. (2008) for a more in depth description. The appendix describes the regulation further.

released by CMS on its website in the Fall of the year before the coverage starts. Through this web site consumers can see the list of plans offered in their region and compare plans on the basis of their financial structure, formulary and pharmacy network.

Similarly, for enrollees it is also useful to introduce a distinction between two groups. Medicare beneficiaries with limited financial resources[9] are entitled a Low Income Subsidy (LIS). I will refer to these individuals as LIS enrollees and to the remaining individuals as regular enrollees. LIS enrollees are about 40% of all the enrollees. Both regular and LIS enrollees receive a subsidy to pay for their premium called the "direct subsidy".[10] Moreover, LIS enrollees also receive an additional subsidy to pay for the premium and, also, discounts for certain expenditures not covered by their plan. These subsidies are paid directly by CMS to insurers and, as discussed below, they represent a key component of plans revenues.

1) Payments to Insurers

Table 1 reports the breakdown of plans reimbursements. The first column shows the premiums paid by enrollees while the remaining four columns refer to payments originating from Medicare. Altogether, payments from Medicare are about 90% of the total reimbursements. Medicare payments can be divided into four categories: (a) direct subsidy, which is paid for every consumer enrolled and is identical for all enrollees up to an adjustment for their risk score; (b) low income subsidy, which is a contribution for consumers of limited financial resources; (c) individual reinsurance, which consists of the payment of 80 percent of drug spending above a certain value known as the "catastrophic threshold"; (d) end of the year reconciliation payments that ensure that the profits/losses made by the sponsor are within certain bounds (defining a "risk corridor").

A major difference between these four sources of reimbursement is that the latter two are exogenous to firms actions. The amount of both the direct and low income subsidies, however depend on prices set by insurers. In particular, each sponsor submits a bid for each of its plans on the first Monday of June each year. On the basis of the bids received,

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[9]In 2009, Medicare beneficiaries with limited resources ($12,510/individual; $25,010/couple) and income below 150% of poverty ($16,245/individual; $21,855/couple) are entitled to the low-income subsidy.

[10]Starting from 2012, for individuals of high income, an extra financial contribution is required.

CMS calculates the direct subsidy in the following way: it takes the weighted average of all bids (the weights are proportional to the plan enrollment share in the previous year) and it multiplies it by a value smaller than one (in 2012, it was 0.63).[11] The plan premium that an enrollee will see on the CMS web site is the difference between the plan bid and this direct subsidy. Therefore, it can happen that some plans appear with a premium of zero dollars. In turn, these premiums are used to calculate the low income subsidy.

2) LIPSA Calculation

Separately for each of the 34 regions into which the US is divided, CMS determines the additional subsidy for LIS enrollees. The dollar amount of this subsidy, known as Low Income Premium Subsidy Amount (LIPSA), is calculated as follows: for a given region, the LIPSA is the weighted average of plans premiums. However, contrary to the direct subsidy where weights are based on total enrollment, since 2009 the weights are based only on enrollment of LIS beneficiaries when calculating the LIPSA. Before then, the system was remarkably different since all plans were essentially weighted equally in the calculation of the LIPSA.[12]

As shown by Table 1, a substantial increase of the LIS reimbursements, amounting to $3.1 billion, occurred contemporaneously with the change in the method of calculating the LIPSA that occurred in 2009. Indeed, the new weighting method significantly reduced the weights of MA-PDs that typically have both low premiums and few LIS enrollees. The effects of this reform on the LIPSA weight is further described in Table 2 which reveals both the marked increase in the LIPSA weights concentration after 2008 and the greater concentration of the LIPSA weights relative the national average weights. These latter weights (reported in the first block of Table 2) are on average 0.045% and, of all the 8,070 PDPs, only 8 plans have

[11] A slightly different weighting system was used for the first two years of the program. See the appendix.

[12] More precisely, the details of how the LIPSA is calculated have changed over time: (a) for 2006 and 2007, all PDPs were assigned an equal weight, while the weight of MA-PDs was proportional to their enrollment in the previous year; (b) for 2008, a weighted method was used in which 50% of the weight was assigned with the same method of 2006 and 2007 and the remaining 50% was assigned to a weighted average of PDP and MA-PD bids with weights proportional to total enrollment (in the previous year); (c) for 2009, the benchmark was calculated as the weighted average of PDP and MA-PD bids with weights proportional to LIS enrollment (in the previous year); (d) from 2010 onward, the calculation is identical to that in 2009 with the only exception that MA-PD bids are considered before the application of a rebate for Part A/B. Finally, in all years, in case the value calculated as above results in something lower than the lowest PDP premium for that region, then this lowest PDP premium becomes the LIPSA.

a weight above 1%. In contrast, the LIPSA weights (second and third blocks of Table 2) are on average always greater than 1% and, starting from 2009, the highest 5^{th} percentile of plans has a weight above 20%, with a maximum of 63.99%.

3) Random Reassignment

The last key aspect of the regulation concerns how LIS enrollees are allocated to plans. Contrary to regular enrollees, LIS enrollees typically do not choose their plan but are assigned to it. For the first year of operation of Part D in 2006, the Social Security Act mandated the initial enrollment of LIS individuals into PDPs with premiums no greater than the LIPSA.[13] Using its authority, CMS specified that for each region this assignment was performed by allocating at random all LIS enrollees across all firms that had at least one basic plan with a premium at or below the LIPSA.[14] For a firm with more than one eligible plan, a further round of randomization took place to allocate LIS enrollees assigned to this firm among its eligible plans. With a few exceptions described below, this random assignment has been repeated in each of the following years to assign new LIS enrollees.

For each year after 2006, LIS enrollees are subject to reassignment if they are enrolled in a plan that will have a premium above the LIPSA in the following year. However, in this case the reassignment is slightly more complex. First, if the plan that will have a premium above the LIPSA belongs to an insurer that in the same region offers some other basic plans that will have a premium at or below the LIPSA, then the LIS enrollees are reassigned at random within the same firm to these other plans. Second, not all LIS enrollees are reassigned but, instead, CMS reassigns only those that: (a) maintain their status of full LIS receivers[15] and (b) never opted out of a plan to which CMS assigned them in the past (unless their plan was terminated, in which case they are again reassigned). Individuals who violate condition (b) are referred to as "choosers". Opting out to choose a plan can be done at any time during the year. For choosers, every year CMS sends a letter to remind them that they need to act

[13]See section 1860D-1(b)(1)(C) of the Social Security Act.

[14]More precisely, for a plan to qualify for a share of randomly assigned beneficiaries, it must meet both design and premium requirements. Only PDPs that have a premium below LIPSA and that are designed as a standard benefit, or actuarially equivalent to the standard benefit, are eligible for the assignment.

[15]Individuals eligible for a partial premium subsidy are not subject to reassignment.

on their own to avoid paying a positive premium, but no automatic reassignment occurs.[16]

The enrollment figures in Table 3 show the relevance of the random reassignment of LIS enrollees. Across the sample years, between 5.8 million and 7.7 million US elderly were potentially subject to reassignments. The number of those enrollees for which the random reassignment occurs varies substantially from year to year and it peaks in 2008 with about 2.5 million reassignments. Since recent reforms are expanding the number of enrollees that will be eligible for the LIS and since, under certain conditions, even LIS choosers can return to random reassignment, reassignments will potentially remain a major feature of this market. Furthermore, as the example of CIGNA in Section 2 revealed, random reassignments often occur within plans of the same insurer. Indeed, Table 4 reveals that, within the same region and year, it is common for insurers to have multiple plans with a benefit structure eligible to receive LIS enrollees. In 2011, for instance, there were 36 instances of insurers having two such plans in the same region and year. This value for 2011 is lower than that recorded in all other years and this is due to a change in regulation aimed at requiring firms to have just one basic PDP per region. Nevertheless, firms using different brand names for their plans were allowed to keep one basic plan per brand and this explains why the value recorded in the table is not zero. The increase observed from 2011 to 2012 is due to an increase in firms with multiple brands that originated from a series of mergers.

Finally, although the reassignment process was designed to limit the risk that LIS individuals would have to pay positive premiums, it may harm continuity in coverage. Reassigned individuals may have to change their pharmacy and, possibly, even drugs. For this reason, CMS introduced in 2007 and 2008 (on a provisional basis) and from 2011 onward (on a permanent basis) a *"de minimis" policy* that provides the opportunity for those plans with premiums above the LIPSA by just a small amount to avoid losing their LIS enrollees by lowering the premium down to the LIPSA for only their LIS enrollees.[17] Six States went even

[16] Plan choices made on behalf of LIS enrollees by "authorized representatives", such as some State pharmacy programs, are treated as individual choice and so cause an exit from the yearly re-assignment process.

[17] For the option to apply, the maximum amount by which the premium could be greater than the LIPSA was set, respectively, to \$1 in 2008 and \$2 in all the other years. Thus, for instance, in 2011 a plan with premium within \$2 above the LIPSA could decide to keep its LIS beneficiaries by accepting to get reimbursed by Medicare a premium equal to the LIPSA.

further in limiting the role of random reassignments by introducing forms of "beneficiary-centered" assignment. However, only Maine essentially replaced the random assignment system with a system matching LIS enrollees to plans based on past consumption of drugs.

4 Data

The dataset for this study consists of data released by CMS on all Medicare D plans offered between 2006 and 2011. These plan-level data allow us to observe enrollment (separately for regular and LIS enrollees) and several other plans characteristics. The main ones are: the basic and enhanced components of the premium, the type of PDP and MA-PD plan, the deductible, the type of coverage in the gap, the identity of the plan sponsor (i.e., the insurance company), the drug formulary and the pharmacy network.

In Table 5, I report some summary statistics for the sample that will be used for the main set of regressions. The data are aggregated at region and year level because the analysis will mainly concern the yearly difference in the average premium across regions. The sample covers the 34 geographical regions and, since I focus on first differences, the years covered range from 2007 to 2011. This implies a sample size of 170 region/year data points.

1) Main dependent variables

Log difference of basic premiums. The main dependent variable used is the difference (in logs) of the average basic premium in a region between year t and year $t-1$. The average basic premium, which I denote $b.premium$, is calculated for region j at time t, (j,t) in short, by taking the weighted average of the basic premium of all the plans offered in (j,t), where the weight of each plan is its share of the total enrollment in (j,t). I denote the log difference as $\Delta \ln(b.premium)$. Table 5 indicates that the mean growth rate of premiums is 2.4%.

Log difference of Medicare premiums. The second dependent variable considered is identical to the first one with the only differences that: (i) instead of using the basic premium it uses the portion of the premium paid by Medicare (i.e., the minimum between the basic premium and the LIPSA) and (ii) the weights associated with each plan equal their share of LIS enrollees in (j,t). Thus, while the former variable measures the average premium, regardless of who pays it, this variable measures the average premium paid by Medicare. I denote the variable in levels as $m.premium$ and in log differences as $\Delta\ \ln(m.premium)$.

Log difference of total premiums for regular enrollees. The third dependent variable considered is again identical to the first one with the only differences that: (i) instead of using the basic premium it uses the total premium and (ii) the weights associated with each plan equal their share of regular enrollees in (j, t). Thus, this variable measures the average total premium paid by regular enrollees. I denote the variable in levels as $r.premium$ and in log differences as $\Delta\ \ln(r.premium)$.

Therefore, the first measure, $\Delta\ \ln(b.premium)$, considers the basic premium regardless of whether it is paid by Medicare or by enrollees. The second measure, $\Delta\ \ln(m.premium)$, considers only the premium that Medicare pays. The third measure, $\Delta\ \ln(r.premium)$, considers the total (i.e., basic plus enhanced components) premium paid by regular enrollees. Figure 2 reports the evolution over the sample period of the three measures of premium (basic, Medicare and total) aggregated at national level using enrollment shares.

2) Independent variable

Concentration of LIPSA weights. To capture the idea of when it should be both easy and lucrative to manipulate the LIS, I construct a variable that equals the sum of the 4 highest LIPSA weights among all the PDPs offered in (j, t). I denote it as $wLIS4$. Relative to other possible proxy measures for the incentive to manipulate the LIS, this variable is both transparent and highlights that with a high LIPSA weight distributed among very few plans, altering the LIS is easier as it requires modifying a small number of premiums.[18] This variable has a mean of 41.5% and ranges from its lowest value of .03 in 2007 in both region 28 (AZ) and 29 (NV), to a maximum of .93 in 2011 in region 1 (ME,NH). Interestingly, the second highest value in the sample, .89, pertains to region 28 (AZ) in 2011. This substantial variation over time experienced by region 28 is predominantly due to how the rules for the LIS

[18] Indeed, $wLIS4$ seems a better proxy for the likelihood of LIS manipulations relative to, for instance, the sum of the LIPSA weights of the 4 firms with the highest LIPSA weights. In fact, if a firm has its high LIPSA weight spread over many plans, it will need to move the premiums of many plans to achieve its desired LIPSA manipulation. In any case, the main results of this study remain qualitatively similar if the independent variable is the one described in this footnote.

calculation changed over time (see Section 3). In Section 5, I will describe how these changes in the regulation are exploited to identify the effect of $wLIS4$ on the outcome variables. The discussions of the instrumental variables used is also deferred to that Section.

Finally, the regression analysis employs various other covariates to control for differences across markets. In particular, I use the (one-year lagged) Herfindahl index and unemployment rate to control, respectively, for each region market structure and economic situation. Furthermore, I use the enrollment-weighted mean of plan age, number of in-network pharmacies and share of active principles covered (relative to all active principles covered by Medicare for the year). As discussed later, the first variable is be useful to control for switching costs, while the latter two serve to control for changes in the mean plan generosity.

5 Empirical Strategy

The main relationship that I seek to uncover is that between changes in the basic premium and the concentration of LIPSA weights. In particular, I assume that the following linear relationship exists and I use the region/year-level dataset described earlier to estimate:

$$\Delta ln(b.premium)_{jt} = \alpha + \beta(wLIS4)_{jt} + \gamma X_{jt} + \delta Q_{jt-1} + \tau_t + \lambda_j + \epsilon_{jt}. \tag{1}$$

The coefficient of interest is β as a positive and significant coefficient for β would support the hypothesis that greater manipulability of LIPSA weights is associated with a faster growth in premiums. In an ideal dataset, we would observe different levels of $wLIS4$ assigned at random to otherwise identical markets. This is different from what is observed in the CMS dataset and, hence, the empirical strategy proposed tries to correct for departures from this ideal setup. The first element of this strategy consists of estimating the above relationship through OLS in which the set of included covariates is gradually expanded. Since premiums for year t are set in June of year $t-1$, I control for both lagged and contemporaneous market characteristics, as also suggested in Dafny et al. (2012). I collect in the matrices Q_{jt-1} and X_{jt} these two sets of characteristics. Among the lagged characteristics in Q_{jt-1}, I consider the market HHI and unemployment rate. The former is particularly relevant because, after the switch to enrollment weighting in 2009, both $wLIS4_{jt}$ and HHI_{t-1} depend on the enrollment concentration at $t-1$. Thus, controlling for the HHI limits the risk that the presence of market power distorts the estimates of β.

As regards the contemporaneous characteristics included in X_{jt}, they are all calculated by weighting plans with their enrollment share at t. In particular, I consider the number of in-network pharmacies and the share of active principles covered as measures of plans generosity at time t. Therefore, they should help in controlling for the cost of the plans offered at time t. Furthermore, I include the age of the plans in the market to account for the possibility that younger plans will experience a faster growth in their premium due to insurers exploiting the consumers' inertia in plan choices. In all regressions I also include year and region fixed effects to control for unobserved characteristics. Finally, I will present all regression models both with and without region-specific time trends which might account for differences in the evolution of plans premiums that are not captured by any of the other covariates included.

Instrumental Variables Approach

The second element of the empirical strategy follows an instrumental variable approach for the identification of β. An IV approach is needed because, absent any manipulation of the LIPSA, the enrollment weighting system mechanically induces a downward bias in the OLS estimate. The reason follows the explanation of enrollment weighting given in Section 2: It is a system based on a moving average that from period to period assigns more weight to the lowest priced plans. Thus, assume that premiums are fixed through time and consider two regions identical in everything except for the fact that at time t one has a much higher LIPSA weights concentration. Enrollment weighting will likely imply that, between $t-1$ and t, premiums will decline faster in the region with the higher LIPSA weights concentration. In fact, since the plans with the highest LIPSA weights are also most likely to be the cheapest when considering all plans within a region, then in the high weights region LIPSA$_t$ will move faster toward the cheapest plans relative to what happens in the other region.[19] Since the

[19] As long as LIS enrollees are not all in a single plan, in which case this plan premium equals the LIPSA.

automatic reallocation of LIS enrollees into cheaper plans tilts the total enrollment shares in favor of the cheapest plans and since the average premium in a region weights plans by their total enrollment, it is likely that the decline in $b.premium_t$ relative to $b.premium_{t-1}$ will be more pronounced in the high weights region relative to the other region. The presence of this potential downward bias is what necessitates the use of the IV. However, this approach has the additional advantage that it might help to correct for another potential source of attenuation bias due to the possible presence of measurement errors in the LIPSA weights.[20]

1) The Penetration of Medicare Advantage Between 2003 and 2006

The IV strategy that I use to estimate β is based on the differential penetration across regions of Medicare Advantage before 2007. Before explaining the relationship between the pre-2007 MA enrollment and the subsequent evolution of $wLIS4$, I will discuss the Medicare Advantage penetration. The Medicare Advantage system introduced in 2003 replaced the previously existing Medicare C. Both the old and the new systems consisted of a market for private health insurance plans that offered to Medicare enrollees the benefits of the original Medicare plan (Parts A and B). However, Medicare Advantage plans were meant to be more attractive to consumers because they were also allowed to offer coverage for prescription drugs. Because of this feature, all the Medicare Advantage plans offering drugs became part of Medicare D when this program started in 2006. In particular, these plans became those to which I have previously referred to as MA-PDs.

The main instrument that I use measures for each region the share of Medicare D enrollees that in 2006 were enrolled in MA-PDs. More precisely, to allow this variable to have different effects through time, I interact it with year dummy variables and use as instruments these interacted variables. Table 5 reports that the mean and standard deviation of the 2006 MA-PD share are, respectively, 20.9% and 14.6%, while Figure 3 is a heat map dividing its distribution in three tertiles.[21] The different geographic penetration that emerges from this figure is predominantly driven by various State mandates that, starting in the early

[20] A likely source of measurement error is due to the fact that Medicare anonymizes the enrollment of all plans with less than 11 enrollees by reporting an asterisk instead of the number of enrollees. For all these low-enrollment plans, I assumed that their enrollment was equal to 5.

[21] The dispersion in the 2006 MA-PD share is substantial ranging from almost 60% in Arizona and Nevada to less than 4% in Mississippi and Maine.

1990s, fostered enrollment into Medicare Managed Care (MMC) plans, part of the Medicare Advantage system.[22] Therefore, it seems reasonable to argue that the MA-PDs penetration in 2006 is exogenously determined relative to the main relationship between LIPSA weights and premium growth that I seek to study, especially after market fixed effects and time trends are controlled for.

Nevertheless, to strengthen the confidence in the exogenous nature of the instrument used, I also replicate the analysis using the Medicare Advantage shares in 2003, 2004 and 2005. Table 5 reports summary statistics for these three variables. The mean shares are different from the 2006 one because, while for 2006 I computed the share of Medicare D enrollees in MA-PDs, for 2003-2005 I computed the share of enrollees in MA plans out of the entire population of medicare eligibles in the region. Since not all medicare enrollees take up Medicare D, the smaller denominator bolsters the mean 2006 share relative to that of the other years. Nevertheless, the geographic variation exhibited by these variables is similar to that in Figure 3 and, indeed, the estimates obtained using any MA share are rather similar.

2) LIPSA Weights and the Prior Medicare Advantage Penetration

In addition to being likely exogenous, the 2006 MA-PD share is also strongly associated with the evolution of the LIPSA weights. This is most clearly seen visually throughout the four plots of panel (a) in Figure 4: A larger MA-PD share in 2006 is associated a lower value of $wLIS4$ in 2007 and 2008 and a higher concentration of weights in 2009 and 2010 (and 2011, not in the figure). The reason for this reversal from 2009 onward is closely connected with the difference between equal weighting and enrollment weighting discussed in Sections 2 and 3. In fact, before 2009 *all* the PDPs within the same region were essentially weighted equally. Since their cumulative weight had to be equal to the share of total enrollment in PDPs in the region, high MA-PD enrollment meant a low weight for each PDP. Moreover, since regions with high MA penetration had also a particularly large number of PDPs in the first years, this further reduced the individual weight of each single PDP.

The reversal observed from 2009 onward is the result of the change to enrollment weighting. Regions with a high MA-PD penetration in 2006 had registered low LIPSA values in the

[22]Duggan and Hayford (2011) describe in detail the evolution of MMC mandates between 1991 and 2003.

first years because the near-zero premiums of most MA-PDs had lowered the amount of this subsidy. This necessarily implied that only few PDPs had premiums low enough to qualify for the random assignment of LIS enrollees. Therefore these few qualified plans enrolled a large share of LIS enrollees and, hence, once the LIPSA weights were switched to previous-year LIS enrollment they were suddenly assigned significantly higher LIPSA weights. The fact that this change in the distribution of weights across regions is due to a national reform suggests that the four instruments that I construct by interacting the 2006 MA-PD share with indicators for the years 2007 to 2010 are exogenous. Moreover, the discussion in this section suggests that the instruments should have a strong effect in the first stage regression. The next Section quantifies exactly both this effect and the relationship between the 2006 MA-PD share by reporting the results of the first stage, reduced form and second stage regressions for different choices of the set of covariates. Nevertheless, 'visual IV'presented by panels 9a) and (b) of Figure 4 already shows the essence of my IV strategy. The comparison of the two panels reveals that for both the first stage and the reduced form the relationship with the 2006 MA-PD share flips sign as we move from 2008 to 2009. Therefore, the effect that the IV estimates in the next section will capture is due to the LIS rule changes occurred in 2009 and not to pre existing trends.

6 Results

This Section describes first the main findings on the effect of the LIPSA weights concentration on the basic premium growth. The same type of analysis is then repeated for the Medicare paid premium and the regular enrollees premium. The final set of results, instead, looks at individual plan premiums to analyze some of the mechanisms behind LIS distortions.

1) Main Results

To assess the effect of the LIPSA weights concentration on the growth of basic premiums, I begin from estimating via OLS Equation (1) above. As discussed in the previous section, a positive and statistically significant estimate for β would imply that premiums grow faster when the LIS is more prone to manipulations. The estimates reported in the first 6 columns of

Table 6 confirm that the OLS estimates for β are indeed positive and statistically significant. Adding controls for lagged market characteristics (columns 3 to 6), as well as adding controls for contemporaneous market characteristics (columns 5 to 6) slightly increases the magnitude of the estimated coefficient. However, the largest point estimate for the OLS is obtained when in addition to the complete set of contemporaneous and lagged covariates, region specific time trends are also included in the model specification (column 6). In particular, the OLS estimates range from .27 for the model with only region and year dummy as covariates to .35 for the model with all covariates and time trends. Given an estimate of .35, a one standard deviation increase of $wLIS4$ would imply an increase in $\Delta ln(b.premium)$ of 8.7%. This is a large effect if compared with a sample mean of $\Delta ln(b.premium)$ of just 2.4%. As regards the estimates of the other regression covariates, their lack of statistical significance might be due in part to the reduced sample size. Alternatively, as argued in the study of Duggan and Scott Morton (2010, 2011), the reason might be that the increases in premiums in Medicare D is hard to explain using conventional measures related to the growth in plan costs for drugs. In the final part of this Section, I will return to this issue to argue that the reason is also due to the small differentiation of basic PDPs relative to the enhanced ones.

A noticeable feature of the OLS estimates is that they tend to grow larger as the regression specification includes more covariates. This seems to support the idea that the OLS coefficient might be downward biased. To account for this issue, the last 6 columns of Table 6 present IV estimates obtained via 2SLS. The specification of the regression models used corresponds to the specification of the 6 models estimated via OLS. The effect of the LIPSA weight concentration is estimated to be positive and statistically significant. Moreover, relative to their OLS counterparts, all 2SLS coefficients are larger. Although this seems to support the idea of a downward bias for the OLS, for most of the regression models the OLS estimates lie within the 95% confidence interval of its 2SLS counterpart. Focusing on the model that includes all covariates and time trends for each region, a one standard deviation increase in $wLIS4$ is now estimated to induce an 18% increase in the basic premium growth.

The set of instruments in each one of the 2SLS regressions is composed of four instruments obtained by interacting the MA-PD share in 2006 with dummy variables for 2007, 2008, 2009 and 2010. Although Section 5 described in detail why these instruments should be correlated with $wLIS4$, a natural concern of an IV approach is the strength of the first stage relationship. The first 6 columns of Table 7 show the first stage regressions corresponding to the 6 specification models of Table 6. These estimates seem to suggest that there is a strong association between $wLIS4$ and the instruments. Indeed, for each regression the R^2 exceeds 95%. Moreover, for each model there is at least one instrument that has a statistically significant coefficient. Given the high degree of correlation between these instruments, all generated from the 2006 MA-PD share, multicollinearity is likely one of the sources of lack of significance. The regressions also confirm the change in the relationship between 2006 MA-PD shares and $wLIS4$ that occurred in 2009. While the instruments obtained with the interactions with 2007 and 2008 have negative coefficients, the remaining two have positive coefficients. In a similar way, in the last 6 columns of Table 7 I assess the performance of the reduced form regressions. The results are similar to those described for the first stage, but the relationship appears less strong than the one in the first stage. In particular, when region specific time trends are included, the instruments are significant only if neither contemporaneous nor lagged covariates are included. For the four remaining models, instead, at least one of the instruments is statistically significant. Furthermore, the R^2 is now lower ranging from 49% to 67%. These findings suggest performing a more in depth exploration of the robustness of the 2SLS estimates agains the risk of having too many weak instruments.

2) Robustness of the IV Estimates

The first exercise that I conduct to investigate the reliability of the 2SLS estimates, is to compare them with LIML estimates. The results of this comparison are presented in the top four rows of Table 8. When the 2SLS uses too many weak instruments, the estimated coefficient is biased toward the OLS coefficient. The LIML coefficient, instead, despite having larger variance, will typically yield a point estimate that is nearly unbiased. The findings reported in Table 8 reveal that the 2SLS and LIML estimates are quite close for all the model specifications analyzed. Furthermore, after the 2SLS and LIML the table reports the value of the F statistic of the excluded instruments for each one of the six first stage models. The high values of the F reported in the table, all above the rule of thumb value of 10, are suggestive of the appropriateness of the instruments chosen.

The second type of robustness check that I conduct regards the instruments exogeneity. In particular, the claim that instruments are exogenous relative to the main relationship studied can be made more forcefully for MA shares of periods further away from the sample analyzed. However, the further I go back in time with Medicare Advantage penetration, the weaker the first stage relationship I expect to find. I consider the period from 2003 to 2005, which is the entire period between when Medicare Advantage was established and when Medicare D started. For each of these years I calculated the MA penetration in each of the 34 regions and I interact this variable with dummies for the years 2007 to 2010 to produce four instruments analogous to those used in the previous IV regressions. Using each of these three sets of instruments, I repeat the IV analysis described earlier using both 2SLS and LIML. The results are presented in the bottom part of Table 8. Overall, these estimates seem to confirm the positive and significant effect of $wLIS4$. Nevertheless, the estimated coefficient is not statistically significant whenever region specific time trends are included. Moreover, even for the specifications in which the estimate is significant, the coefficient magnitude is smaller relative to that of the 2SLS in the main set of regressions and closer to the OLS estimates. Similarly, the magnitude also decreases as we move from the 2005 MA instruments to the 2003 MA instruments. This seems consistent with the worsening of the first stage as we move further from 2006. Indeed, the F statistic, at least for the two models without lagged and contemporaneous covariates, fall below the critical value of 10.

3) Results for Medicare and Regular Enrollees Premium Changes

Although the previous results revealed increases in the basic premium associated with the LIS manipulability, many regular enrollees (i.e., those not receiving the LIS) enroll in enhanced plans and, so, are more concerned about their total premium, given by the sum of the basic and enhanced premium components. In contrast, for the public cost of the program, the most relevant measure is that of the premium paid by Medicare for the LIS enrollees, which equals the minimum between their plans basic premium and the regional LIPSA. Therefore, in Table 9 I repeat the OLS and 2SLS using the Medicare paid premium and the total premium for regular enrollees as dependent variables. The specifications considered are those including the full set of covariates, with and without region specific time trends. Consistent with the previous results, the IV estimates are larger than the corresponding OLS ones. However, the main finding is that there is a clear difference between the effect of $wLIS4$ on these two measures of premiums. While for the Medicare paid premium the coefficients are larger than those estimated for the basic premium and always significant at the 1% level, for the regular enrollees total premium the estimate is smaller in size and never significant at the 5% level. These results seem to suggest that LIS distortions are particularly harmful for the part of the program cost faced directly by Medicare. Indeed, given the point estimate of .971, a one standard deviation increase of $wLIS4$ is estimated to increase the growth in the Medicare paid premium by 24%. Instead, the lack of a clear effect on the total premium faced by regular enrollees suggests that insurers pricing strategies might be able to exploit the endogeneity of the LIS by specifically targeting the LIS enrollees population. However, since the regulation forbids plans open only to one type of enrollees, targeting is imperfect and so regular enrollees are also likely to suffer from the LIS distortion. I will next explore how this distortion manifests itself at the level of individual plans premium.

4) Plan-level Findings

In addition to setting premiums, the regulation entitles insurers to take several actions. For instance, as seen in the example on CIGNA, insurers can consolidate their plans. Instead of trying to account for all the possible strategies that insurers might use to distort the LIS, in this section I present a descriptive analysis of two aspects that are potentially relevant for various types of manipulation schemes: The decision to drastically raise or reduce a premium from one year to the next and the premium to set for newly entering plans.

A) Discontinuous Premium Increases and Decreases

The theoretical example in Section 2 offered the clearest illustration of why an insurer might want to drastically raise or reduce the premium of one or more of its plans. Therefore, the first set of plan-level correlations that I present here looks at the decision to submit extremely higher/lower premiums from one period to the next. In particular, for every plan I calculate the percentage change in its price from one year to the next. Then I create dummy variables to indicate which of these changes qualify as "jumps". In Table 10, I consider 3 cases: first, a dummy equal to 1 when the premium increase is more than 50%; second, a dummy equal to 1 when the increase is more than 75%; third, a dummy equal to one when the decrease is more than 40%. For each of these three variables, I estimate the probit model:

$$Pr(Premium\_Jump_{ijt}) = \Phi[\alpha + \beta_1(wLIS\_Firm)_{ijt} + \beta_2(Eligible\_Firm)_{ijt} + \beta_3(Solo\_Basic\_PDP)_{ijt} + \gamma X_{ijt} + \tau_t + \lambda_j + f_i],$$

where i indexes the plan, j the region and t the year. $Premium\_Jump_{ijt}$ is one of the three dummy variables and Φ is the CDF of the unit-normal distribution. The descriptive analysis focuses on three dependent variables: The first is $(wLIS\_Firm)_{ijt}$ which is the sum of the LIPSA weight of all plans owned by the insurer offering plan i (in (j, t)). Since firms with higher weight have a greater incentive to increase the LIPSA, then β_1 should be positive when the dependent variable is a positive jump and negative for negative jumps. The second main variable is $Eligible\_Firm_{ijt}$, that is a dummy equal to 1 if the plan i is not eligible for LIS enrollees but the same insurer has at least one eligible plan in (j, t). Since making a positive jump is only beneficial when some other partner plan is eligible for LIS enrollees, β_2 should be positive for upward jumps and negative for negative jumps. The third variable is $Solo\_Basic\_PDP_{ijt}$, that is a dummy equal to 1 if the plan is a basic PDP and if in $t-1$ the firm did not have any eligible plan (i.e., no basic PDP below the LIPSA). If a firm is interested in LIS enrollees, then given that in $t-1$ it was ineligible, in t it is more likely to decrease its premium. Hence, β_3 should be negative for positive jumps and positive for negative jumps. The regressions also include dummy variables to control for years (τ_t), regions (λ_j) and the identity of the 15 largest firms (f_i). Finally, the matrix X_{ijt} contains additional covariates and it differs across the specifications analyzed.

Table 10 reports the results of six probit regressions, two for each one of the three dependent variables. For the models in the first three columns, X_{ijt} only contains dummies for enhanced plan and for t greater than 2008. For the remaining three models, instead, X_{ijt} also includes the plan age, the share of active principles covered and the number of in-network pharmacies. The estimates reported in the table are the marginal effects and they reveal that the estimates of β_1, β_2 and β_3 are broadly in line with the expectations. In particular, across all the 6 regressions β_1 is significant and its sign lends support to the idea that a discontinuous premium raise is associated with an insurer having a greater LIPSA weight. Furthermore, the estimate of β_2 suggests that an upward jump is more likely when the firm offering plan i remains eligible due to offering an alternative plan eligible for LIS enrollees. Instead, an insurer with a greater LIPSA weight will not adopt drastic reductions of its premiums. The estimates of β_2 indicate that, however, such drastic reductions are likely when the plan considered is the only basic PDP of the insurer in (j, t) and the firm did not have any eligible plan in $(j, t-1)$. This also confirms that, even absent any direct manipulation of the LIS, firms actively try to be eligible for the LIS enrollees.

B) Initial Premium of Entering Plans

The final set of correlations analyzed describes how the LIPSA is associated with the premium of newly entering PDPs. A certain concentration of premiums near the LIPSA is to be expected for basic PDPs whenever insurers are exploiting the fact that LIS enrollees are price inelastic up to the value of the LIPSA. Instead, no such concentration is expected for enhanced PDPs. Figure 5 reports separately for basic and enhanced PDPs the difference between their premium and the LIPSA for each year in the sample. Thus, a value of zero implies that in the year in which it was introduced, the PDP had a premium identical to the LIPSA in its region. The most relevant years on which to focus are those between 2007 and 2010. In fact, in 2006 all PDPs offered were newly entering, while in 2011 the separation between basic and enhanced premiums is driven by a new regulation forcing insurers to differentiate further their enhanced plans from their basic ones. For the years between 2007 and 2010, the figure seems to suggest a greater concentration of basic PDP premiums closer to the LIPSA. Furthermore, in both 2008 and 2010 one can observe enhanced plans entering at premiums substantially lower relative to the LIPSA than basic plans. This suggests insurers followed different strategies in pricing their basic and enhanced plans. The former were used to extract the maximum premium paid by Medicare, that is the LIPSA. The enhanced plans, instead, could have been used to perform the *bargain-then-ripoff* strategies described by Ericson (2010): An enhanced plan entering with a very low premium is appealing for regular consumers, but when in the following years it raises its premium their inertia prevent them from leaving it.

Further evidence in support of the difference between the determinants of basic and enhanced PDPs entering premiums is presented in Table 11. The estimates in this table are obtained by estimating via OLS the following model:

$$Premium_{ijt} = \alpha + \beta LIPSA_{jt} + \gamma X_{ijt} + \tau_t + \lambda_j + f_i + \epsilon_{ijt}$$

The coefficient of interest is that on the LIPSA. A positive and significant β for basic PDPs would be supportive of the idea that when deciding the entering premium of these plans insurers take into account the LIPSA. Although merely descriptive, the correlations in this table reveal interesting patterns in the data. In fact, not only is the coefficient on the LIPSA statistically positive and significant for entering basic PDPs (both when considering all basic PDPs and the subsample of those entering below LIPSA), but the same coefficient estimated using the corresponding sample of enhanced PDPs is not significant. There is mixed evidence, instead, about whether the entry premium of basic (enhanced) PDPs is linked to the premium of the cheapest basic (enhanced) PDPs available in the region. Indeed, the coefficient on a variable measuring the 5^{th} percentile of the premium distribution flips sign and significance. One final aspect of interest in this Table regards the coefficients on the measures of plans generosity used throughout this paper: The number of in-network pharmacies and the share of covered active principles. The fact that, especially for the latter coefficient, the estimate is large and significant only for enhanced PDPs, while it is negative and not significative for basic PDPs suggests that basic PDPs are too similar in terms of their generosity. This result is likely due to a regulation imposing minimum requirements in terms of the therapeutic conditions covered by the active principles offered and it helps to explain why in the main set of regressions no significant effects of plans generosity on premium changes were found.

7 Conclusions

This study has presented an analysis of how the low income subsidy distorts firms pricing behavior in Medicare Part D. The complexity of this market implies that firms are subject to numerous and possibly conflicting incentives. Therefore, there is still an open debate regarding the causes of the premiums increases. The low income subsidy, which had received little attention in the previous studies, has been shown to be an important source of distortions. The evidence presented in this study not only supports the hypothesis that the manipulability of the LIS is associated with a faster rate of premium growth, but that the increase is large in magnitude amounting to an increase of 8.7% in response to a one standard deviation increase in the variable measuring the manipulability of the LIS. This suggests that the increase in the average concentration of LIPSA weight, that passed form a value of .07 in 2006 to a value of .67 in 2011, can explain 58% of the increase in the (population weighted) average basic premium, that in this same period passed from \$20.5 to \$27.34.

These findings are important because they complement those of Duggan and Scott Morton (2010, 2011) and Ericson (2010) about the sources of premium growth. Moreover, they also complement the vast literature on the consumer choice of plans in Medicare D by showing that an efficient allocation of consumers to plans requires not only helping consumers to pick plans, but also fixing premium distortions. Under the current regulation, plans premiums unlikely reflect the true underlying cost conditions and, hence, cannot guarantee efficiency.

This study also has relevant implications for both future research and policy reforms. As regards the former, having identified the LIS as a source of distortions implies that an important avenue for future research would be to analyze alternative systems to structure the LIS. Moreover, other types of distortions not analyzed in this paper but that might be fruitfully studied are those concerning the direct subsidy and the formularies composition.

Finally, as regards the policy implications, the conclusions of this study offer an argument in favor of the various proposals that in recent years have been put forward to drastically reform the LIS system. They include separating the LIS and regular enrollees markets and, possibly, switching fto a beneficiary centered assignment for the LIS enrollees or even returning to the Medicaid drug coverage system. As the cases of the LIBOR and ABAs have clearly shown, no lasting effect can be expected from milder reforms aimed, for instance, at merely reducing the number of plans that each insurer can offer in a market.

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Table 1: Aggregate Plans Reimbursement Amounts

	Enrollees	Medicare				
Year	Premiums	Direct Subsidy	LIS	Rein-surance	Risk Sharing	Total
2006	3.5	17.3	15.1	8.6	-	44.5
2007	4.1	18.4	16.5	7.1	-0.7	45.4
2008	5.0	17.5	17.4	6.7	-1.3	45.3
2009	6.1	18.8	20.3	11.4	-0.1	56.5
2010	6.7	19.9	20.9	10.5	-0.7	57.3
2011	7.3	20.1	22.3	12.8	-1.0	61.5

All amounts are in US$ billions. The first column reports the total yearly premiums paid by enrollees. The remaining columns report the payments from Medicare: the direct subsidy (which includes risk adjustment payments), the low income subsidy (which includes both the premium subsidy and contributions for drug copayment), reinsurance payments (80% of the expenditures above the catastrophic threshold) and risk sharing payments according to the risk corridor (negative amounts are net gain-sharing receipts from plans and may include the delayed settlement of risk sharing from prior years). Data from Table IV.B11 of the Trustees of Medicare 2012 Report.

Table 2: Weights of the PDPs

Weights of All PDPs, 2007-2011

	National Weights		LIPSA Weights 2007-2008		LIPSA Weights 2009-2011	
	Full Sample	≥ 1%	Full Sample	≥ 1%	Full Sample	≥ 1%
Average	0.045	1.144	1.453	1.815	2.333	7.099
SD	0.091	0.099	1.154	1.284	5.037	6.938
5thPerc	0.000	1.014	0.594	1.063	0.000	1.151
25thPerc	0.008	1.076	0.870	1.298	0.039	2.174
50thPerc	0.023	1.142	1.271	1.543	0.196	5.115
75thPerc	0.038	1.184	1.649	1.751	1.873	9.267
95thPerc	0.168	1.336	2.783	3.638	12.490	20.895
99thPerc	0.484	1.336	6.695	8.268	23.849	33.896
N	8,062	8	3,690	2,413	4,372	1,365

Top 8 Weights of PDPs, 2007-2011

	National Weights		LIPSA Weights 2007-2008		LIPSA Weights 2009-2011	
	Year	Weight	Year-Region	Weight	Year-Region	Weight
1st	2011	1.336	2008-NH,ME	19.757	2010-NV	63.989
2nd	2011	1.222	2008-AK	18.038	2011-HI	52.369
3rd	2010	1.147	2008-NJ	13.462	2011-NH,ME	51.002
4th	2011	1.147	2008-DE,DC,MD	12.800	2011-MO	44.032
5th	2010	1.138	2008-IL	12.343	2011-AZ	43.001
6th	2011	1.083	2008-GA	11.182	2011-AZ	42.200
7th	2010	1.070	2008-HI	10.967	2010-AZ	39.310
8th	2009	1.014	2008-IN,KY	10.620	2010-NH,ME	38.830

Top 8 Cumulative Weights of Plan Sponsors, 2007-2011

	National Weights		LIPSA Weights 2007-2008		LIPSA Weights 2009-2011	
	Firm Year	Weight	Firm Year Region	Weight	Firm Year Region	Weight
1st	UHG 2010	24.7	UHG 2008-AZ	33.2	Coventry 2010-NV	64.7
2nd	UHG 2011	24.4	UHG 2008-CO	30.9	UHG 2011-HI	52.4
3rd	UHG 2009	23.4	UHG 2007-CO	30.4	UHG 2011-NH,ME	51.0
4th	UHG 2008	20.5	UHG 2007-AZ	29.2	Universal 2011-MO	44.3
5th	Humana 2009	19.2	UHG 2008-AK	27.3	UHG 2010-NH,ME	43.7
6th	Humana 2008	16.1	UHG 2008-NH,ME	27.0	UHG 2010-HI	43.7
7th	UHG 2007	15.7	Humana 2008-ID,UT	26.3	HealthNet 2011-AZ	43.1
8th	Humana 2010	12.3	Humana 2008-FL	25.6	UHG 2011-AZ	43.1

The top row of the table has three boxes that report the distribution of both the weights for the calculation of the direct subsidy (left box) and the weights for the calculation of the LIPSA (middle and right box). The distribution across all PDPs as well as that across the subset of PDPs with at least a weight of 1% are reported. The three boxes in the second row report for each distribution the 8 highest values and the corresponding year and region. The three boxes in the last row aggregate the weights by firm and report the 8 firms with the highest weights: The left box reports only the year and the insurer because the weights are calculated on a national basis, the next two boxes, instead also report the interested regions.

Table 3: Number of Enrollees by Type of Enrollee

Year	Tot Enrollment	Tot. Lis	Tot. Lis PDP	Reassigned	Choosers	Choosers PDP	Autoenrolled
2006	20,514,830	8,680,126	8,072,304	0	919,227	311,405	7,760,899
2007	21,856,800	8,709,675	8,004,997	1,140,917	1,035,489	330,811	7,674,186
2008	23,100,694	8,910,216	8,028,385	2,465,767	2,599,930	1,718,099	6,310,286
2009	24,094,520	8,993,114	7,923,221	1,991,534	3,112,388	2,042,495	5,880,726
2010	25,040,622	9,182,241	7,970,999	1,194,565	2,942,184	1,730,942	6,240,057
2011	25,877,644	9,483,357	8,223,792	413,793	2,299,716	1,040,151	7,183,641

Table 3 is based on the same sample used for the summary statistics. The number of choosers and reassigned enrollees is computed following Summer et al. (2010). For 2010, the only year in which the official number of reassigned LIS enrollees is available, there are minor differences between this official number and the values in the table: 1,164,690 reassigned instead of 1,194,565 reported in the table. Moreover, the official value is based on estimates made before the enrollment period ends. Instead, the numbers in the table are computed using the realized enrollment values.

Table 4: Plans of Top Multiplan Firms

Year	1	2	3	4	5	Total
2006	247	246	84	8	5	590
2007	326	302	105	0	0	733
2008	344	250	135	0	0	729
2009	409	230	57	20	0	716
2010	332	350	12	0	0	694
2011	474	72	0	0	0	546
2012	390	126	0	0	0	516
Total	2,522	1,576	393	28	5	4,524

The table reports the number of basic PDPs of the top 20 firms (in terms of enrollment) distinguishing by the number of other basic PDPs of the same parent organization offered in the same year and region (partner plans). Plans in column 1 are those that do not have partner plans. For instance, in 2006 there were 247 basic PDPs of firms that have no other basic PDP in the same year and region Plans in column 2 have exactly one partner plan: In 2006 there are 123 cases of pairs of basic PDPs active in the same year and region and belonging to the same firm. Similarly columns 3, 4 and 5 report the number of PDPs that have respectively, 2, 3 and 4 other PDPs of the same partner organization in the same year and region.

Table 5: Summary Statistics

Variables:	Mean	SD	Median	N
b.premium	22.64	4.888	23.85	170
m.premium	22.8	4.255	23.53	170
r.premium	25.73	6.468	27.18	170
Δ ln(*b.premium*)	0.024	0.085	0.017	170
Δ ln(*m.premium*)	0.003	0.091	0.01	170
Δ ln(*r.premium*)	0.029	0.0901	0.024	170
$wLIS4$	0.415	0.247	0.475	170
No. Firms	25.17	6.339	24	170
No. Plans	145.9	74.81	128.5	170
All Enrollees	705,708	577,732	537,025	170
LIS Enrollees	284,956	245,186	203,167	170
Drugs	0.846	0.0463	0.859	170
Pharmacies	1,221	811.3	1,178	170
Plan Age	2.57	1.128	2.644	170
HHI	.121	.042	.110	170
Unemployment	7.342	2.442	7.169	170
MA-PD Share 2006	0.209	0.146	0.191	170
MA Share 2005	0.112	0.097	0.080	170
MA Share 2004	0.105	0.098	0.069	170
MA Share 2003	0.106	0.099	0.066	170

Summary statistics of the sample used for the main regressions (Table 6 to Table 9). Sample period: 2007 to 2011. The values for the HHI and the unemployment rate are lagged by one year.

Table 6: Regressions for the Growth of the Basic Premium

	OLS						2SLS					
VARIABLES	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
$wLIS4$	0.274***	0.301*	0.275***	0.302*	0.304***	0.352**	0.540**	0.568*	0.650***	0.607*	0.724***	0.696**
	[0.059]	[0.149]	[0.075]	[0.156]	[0.076]	[0.142]	[0.198]	[0.333]	[0.213]	[0.350]	[0.216]	[0.337]
HHI			0.155	0.187	0.087	-0.065			-0.328	-0.149	-0.464	-0.638
			[0.469]	[0.528]	[0.471]	[0.731]			[0.544]	[0.522]	[0.544]	[0.676]
Unemployment			-0.77	-2.81	-0.72	-2.34			-1.35	-2.98	-1.32	-2.22
			[0.0106]	[2.64]	[1.07]	[2.45]			[1.25]	[2.92]	[1.32]	[2.76]
Plan Age					-0.071	-0.055					-0.105	-0.061
					[0.067]	[0.104]					[0.064]	[0.107]
Pharmacies					-0.175	-1.03					-0.199	-1.20
					[1.31]	[1.63]					[1.45]	[1.62]
Drugs					-0.292	-0.293					-0.405	-0.517
					[0.356]	[0.481]					[0.468]	[0.495]
Constant	-0.153***	-0.039	-0.157**	0.025	0.196	0.333	-0.207***	0.051	-0.118	0.173	0.379	0.716
	[0.014]	[0.054]	[0.075]	[0.100]	[0.348]	[0.466]	[0.039]	[0.123]	[0.086]	[0.187]	[0.447]	[0.520]
Region												
Time Trends	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.485	0.646	0.49	0.654	0.502	0.663	0.448	0.627	0.43	0.631	0.428	0.636
Observations	170	170	170	170	170	170	170	170	170	170	170	170

Significance: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by region. All estimates include region and year fixed effects.
For readability Pharmacies has been divided by 10,000 and Unemployment multiplied by 100.

Table 7: First Stage and Reduced Form Regressions

	First Stage: $wLIS4$						Reduced Form: Δ ln($b.premium$)					
VARIABLES	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
(MA-PD2006)*(Y.2007)	-0.187	-0.036*	-0.269*	0.024	-0.275*	0.073	-0.086	0.158***	-0.233	-0.025	-0.238	-0.010
	[0.174]	[0.020]	[0.149]	[0.109]	[0.157]	[0.121]	[0.121]	[0.054]	[0.159]	[0.119]	[0.164]	[0.131]
(MA-PD2006)*(Y.2008)	-0.391**	-0.278***	-0.368***	-0.152**	-0.373**	-0.121	-0.245**	-0.061	-0.338***	-0.198	-0.346***	-0.194
	[0.156]	[0.035]	[0.126]	[0.070]	[0.138]	[0.086]	[0.100]	[0.075]	[0.121]	[0.157]	[0.122]	[0.170]
(MA-PD2006)*(Y.2009)	0.076	0.151	0.18	0.322**	0.182	0.343**	0.059	0.181*	0.043	0.147	0.074	0.167
	[0.166]	[0.126]	[0.158]	[0.132]	[0.176]	[0.134]	[0.111]	[0.096]	[0.114]	[0.121]	[0.120]	[0.128]
(MA-PD2006)*(Y.2010)	0.221	0.259	0.182	0.255*	0.172	0.242	0.078	0.139	0.029	0.075	0.057	0.111
	[0.173]	[0.183]	[0.144]	[0.138]	[0.161]	[0.143]	[0.127]	[0.125]	[0.141]	[0.143]	[0.150]	[0.146]
Region Time Trends	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Unemployment, HHI	No	No	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes
PlanAge, Pharm, Drugs	No	No	No	No	Yes	Yes	No	No	No	No	Yes	Yes
R^2	0.954	0.978	0.965	0.98	0.965	0.982	0.487	0.648	0.515	0.664	0.529	0.67
Observations	170	170	170	170	170	170	170	170	170	170	170	170

Significance: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by region. All estimates include region and year fixed effects.

Table 8: Robustness of the IV Estimates

		[1]	[2]	[3]	[4]	[5]	[6]
MA-PD Share 2006	2SLS	0.540**	0.568*	0.650***	0.607*	0.724***	0.696**
		[0.198]	[0.333]	[0.213]	[0.350]	[0.216]	[0.337]
	LIML	0.543**	0.573*	0.657***	0.615*	0.729***	0.701**
		[0.200]	[0.337]	[0.218]	[0.357]	[0.219]	[0.341]
	F-stat.	26.670	22.700	18.990	19.760	20.410	14.600
	R^2	0.954	0.978	0.965	0.98	0.965	0.982
MA Share 2005	2SLS	0.384**	0.113	0.422**	0.139	0.481***	0.181
		[0.167]	[0.382]	[0.184]	[0.393]	[0.174]	[0.380]
	LIML	0.393**	0.108	0.444**	0.134	0.501**	0.177
		[0.178]	[0.391]	[0.206]	[0.403]	[0.192]	[0.386]
	F-stat.	10	9.134	14.5	13.4	17.44	10.07
	R^2	0.955	0.976	0.963	0.979	0.964	0.98
MA Share 2004	2SLS	0.371**	.	0.402**	0.114	0.460***	0.157
		[0.159]	.	[0.175]	[0.393]	[0.166]	[0.379]
	LIML	0.379**	0.0861	0.421**	0.108	0.478**	0.153
		[0.169]	[0.391]	[0.196]	[0.401]	[0.183]	[0.384]
	F-stat.	9.92	.	13.65	12.7	16.4	9.606
	R^2	0.956	.	0.964	0.979	0.965	0.98
MA Share 2003	2SLS	0.366**	0.0839	0.396**	0.105	0.454***	0.149
		[0.157]	[0.382]	[0.173]	[0.392]	[0.165]	[0.378]
	LIML	0.375**	0.0771	0.415**	0.0991	0.471**	0.145
		[0.168]	[0.392]	[0.194]	[0.401]	[0.182]	[0.384]
	F-stat.	9.963	8.744	13.09	12.21	15.54	9.176
	R^2	0.957	0.977	0.964	0.979	0.965	0.98
Controls							
Region Time Trends		No	Yes	No	Yes	No	Yes
Unemployment, HHI		No	No	Yes	Yes	Yes	Yes
Plan Age, Pharmacies, Drugs		No	No	No	No	Yes	Yes
Number of Excluded Instruments		4	4	4	4	4	4
Observations		170	170	170	170	170	170

Significance: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by region. All estimates include region and year fixed effects. For the MA Share 2004, model [2] could not be estimated via 2SLS because the variance-covariance matrix was highly singular due to the sparsity of the covariates used.

Table 9: Regressions for the Medicare Paid and Regular Enrollees Premiums

	OLS				2SLS			
Dep. Var.	Δ ln($m.premium$)		Δ ln($r.premium$)		Δ ln($m.premium$)		Δ ln($r.premium$)	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
$wLIS4$	0.492***	0.584***	0.129*	0.209	1.024***	0.971***	0.386*	0.292
	[0.119]	[0.172]	[0.0716]	[0.131]	[0.17]	[0.197]	[0.22]	[0.239]
HHI	-0.176	0.357	0.368	-0.19	-0.874	-0.378	0.0316	-0.347
	[0.369]	[1.057]	[0.656]	[0.872]	[0.598]	[1.22]	[0.667]	[0.849]
Unemployment	0.004	-0.007	-0.014	-0.049	-0.004	-0.006	-0.018	-0.048
	[0.010]	[0.024]	[0.013]	[0.029]	[0.012]	[0.026]	[0.014]	[0.029]
Plan Age	-0.0396	-0.103	-0.141	-0.086	-0.085	-0.109	-0.163	-0.0873
	[0.075]	[0.147]	[0.116]	[0.178]	[0.079]	[0.140]	[0.118]	[0.177]
Pharmacies	0.120	-0.12	0.706	0.439	-0.467	-1.49	0.626	0.377
	[1.10]	[1.42]	[1.21]	[1.62]	[1.49]	[1.66]	[1.3]	[1.62]
Drugs	-0.584	-0.348	-0.2	-0.485	-0.728*	-0.621	-0.269	-0.544
	[0.406]	[0.463]	[0.517]	[0.634]	[0.42]	[0.545]	[0.595]	[0.641]
Constant	0.374	0.312	0.238	0.637	0.634	0.804	0.363	0.742
	[0.413]	[0.504]	[0.484]	[0.560]	[0.444]	[0.600]	[0.569]	[0.582]
Region								
Time Trends	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.542	0.712	0.395	0.592	0.428	0.677	0.367	0.591
Observations	170	170	170	170	170	170	170	170

Significance: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by region. All estimates include region and year fixed effects. For readability Pharmacies has been divided by 10,000.

Table 10: Large Changes of Plans Premiums

	Probit					
Dep. Var.	Jump >50%	Jump >75%	Jump <-40%	Jump >50%	Jump >75%	Jump <-40%
wLIS_Firm	0.259***	0.087**	-0.114***	0.262***	0.087***	-0.107***
	[0.060]	[0.039]	[0.036]	[0.059]	[0.036]	[0.033]
LIS Eligible Firm	0.022***	0.020***	-0.001	0.009	0.012*	-0.001
	[0.008]	[0.006]	[0.003]	[0.008]	[0.006]	[0.003]
Solo Basic PDP	-0.021**	-0.025***	0.102***	-0.012	-0.025***	0.097***
	[0.010]	[0.004]	[0.018]	[0.011]	[0.004]	[0.018]
Plan Age				-0.002	-0.016***	-0.025***
				[0.003]	[0.003]	[0.003]
Pharmacies				0.898**	0.256	0.154 ***
				[0.397]	[0.216]	[0.041]
Drugs				0.062	0.067	0.011
				[0.055]	[0.042]	[0.015]
Prob Chi^2	0.000	0.000	0.000	0.000	0.000	0.000
Observations	6,828	6,220	5,621	6,270	5,664	5,196

Significance: *** p<0.01, ** p<0.05, * p<0.1. Marginal effects estimated through a probit regression. All regressions include a constant and dummies for: region, year, enhanced plan, year greater than 2008 and for each one of the 15 largest firms. Sample includes only PDPs. The different sample sizes are due to the fact that for the different dependent variables there are different dummies among those for the 15 largest firms that perfectly predict the outcome and that cause dropping a part of the data. The remaining difference in sample size across different specifications for the same dependent variable is due to the unavailability of the Pharmacy variable. Forcing the samples to have the same size does not qualitatively alter the estimates. For readability Pharmacies has been divided by 10,000.

Table 11: Premium of Newly Entering Plans

	PDPs Entering Below LIPSA		All Entering PDPs	
	Basic	Enhanced	Basic	Enhanced
LIPSA	0.719***	-0.460	0.683***	0.695
	[0.125]	[2.448]	[0.194]	[0.472]
5^{th} Pct. Premiums	0.191**	2.331	-0.015	0.708*
	[0.087]	[3.892]	[0.175]	[0.396]
Avg. Plans Age	0.262	7.390	2.374***	-0.914
	[0.390]	[4.688]	[0.805]	[1.844]
Pharmacies	0.188	-0.205	0.057	0.188*
	[0.296]	[2.10]	[0.344]	[0.101]
Drugs	-9.817	36.08	-3.484	31.22***
	[6.144]	[32.16]	[5.552]	[10.04]
LIS Share Firm	1.395	-15.49*	-2.338**	-4.748
	[0.829]	[8.381]	[0.939]	[3.001]
Tot. Share Firm	16.62	39.37	-15.32	-4.892
	[12.25]	[38.37]	[10.95]	[26.35]
LIS Enrol. Firm	-.061	5.68*	-0.760*	0.310
	[0.215]	[2.79]	[0.415]	[1.730]
Tot. Enrol. Firm	-0.126	-5.53***	0.272	-0.682
	[0.127]	[1.95]	[0.200]	[1.42]
No. PDPs Firm	-0.025*	-0.490	-0.083***	-0.261
	[0.014]	[0.713]	[0.022]	[0.200]
No. PDPs Rivals	0.016*	0.188	0.009	-0.227***
	[0.008]	[0.635]	[0.012]	[0.054]
Constant	-0.265	-46.86	15.14**	4.012
	[6.763]	[38.62]	[6.643]	[16.80]
R^2	0.789	0.967	0.607	0.753
Observations	282	68	471	290

Significance: *** p<0.01, ** p<0.05, * p<0.1. All estimates include region and year fixed effects. Sample period: 2007 to 2010. The definition of the variables in the table not described in the main text is as follows: Consider a plan i entering region j in period t and offered by firm f. Avg. Plan Age is the enrollment weighted average age of the plans of f present in (j, t). LIS Share Firm is the share of LIS enrollees of f in (j, t), calculated relative to the total of LIS enrollees in (j, t). Tot. Share Firm is analogous to the previous variable but uses total enrollment. LIS Enrol. Firm (Tot. Enrol. Firm) is the total number of LIS (all) enrolled in the plans of f in (j, t). No. PDPs Firm is the number of PDPs offered by f in (j, t). No. PDPs Rivals is the difference between the total number of PDPs in (j, t) and No. PDPs Firm. For readability Pharmacies has been divided by 100, while both LIS Enrol. Firm and Tot. Enrol. Firm have been divided by 10,000.

Figure 1: Example: Two Firms and Three Plans

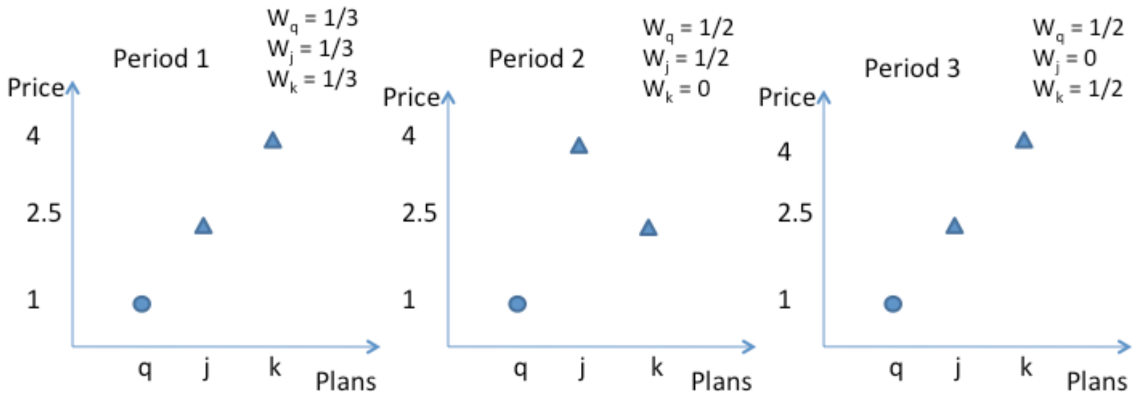
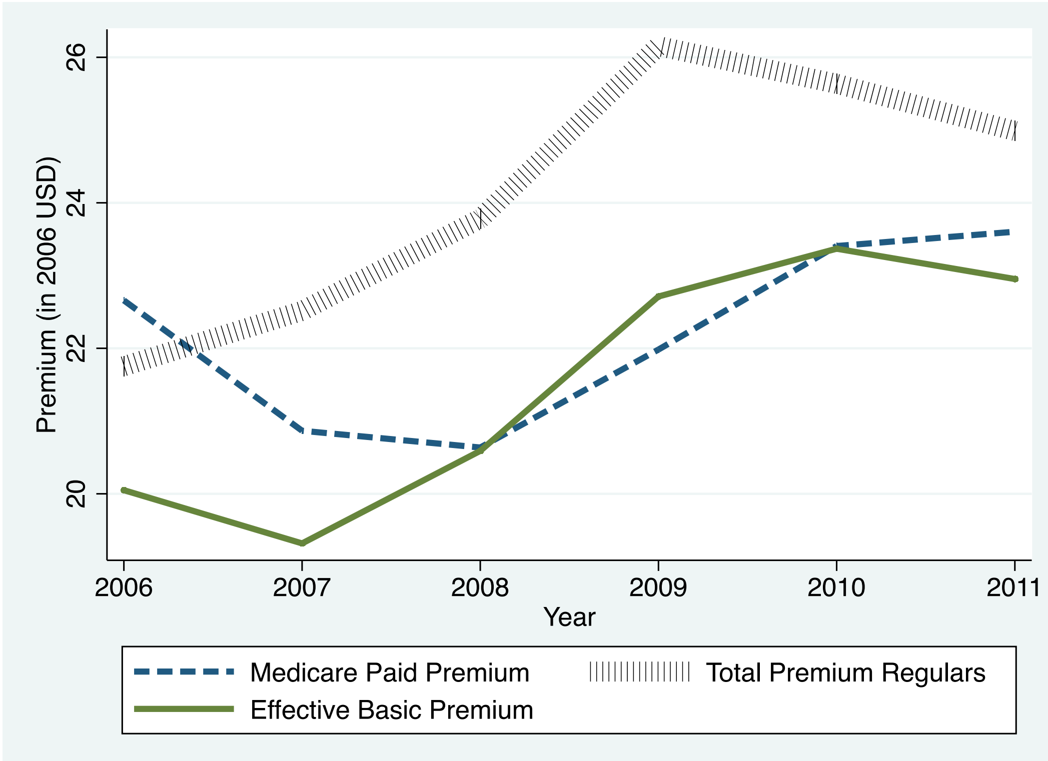


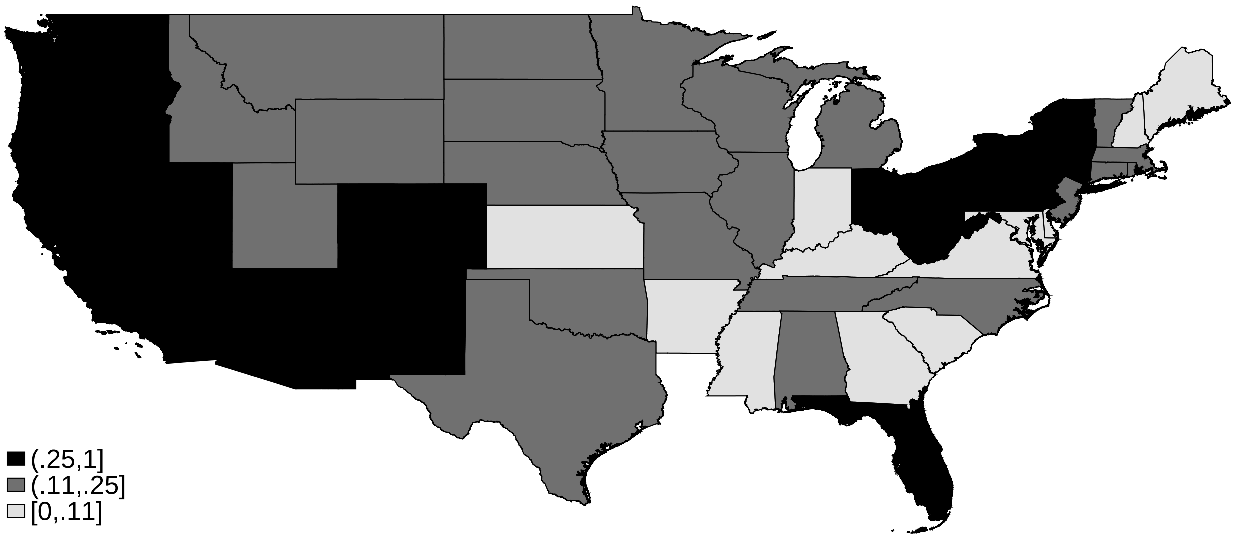
Figure 1 reports the prices of the three plans (q, j, k) in three periods. The two plans indicated by triangles (j, k) belong to the same firm. Plans start in period 1 with equal weights and then in periods 2 and 3 have weights proportional to previous period enrollment. In the first period the LIPSA is 2.5 and the LIS enrollees are shared equally between q and j. In the second period, the prices of q and j keep the LIPSA at 2.5 and all the LIS enrollees of j are moved to k (i.e., they are reassigned within the same firm). In period 3, the roles of j and k are reversed.

Figure 2: Evolution of the Premiums



The figure reports the evolution over time of the three measures of premium (aggregated at national level using enrollment shares): Effective Basic Premium corresponds to *b.premium*, Medicare Paid Premium to *m.premium* and Total Premium Regulars to *r.premium*.

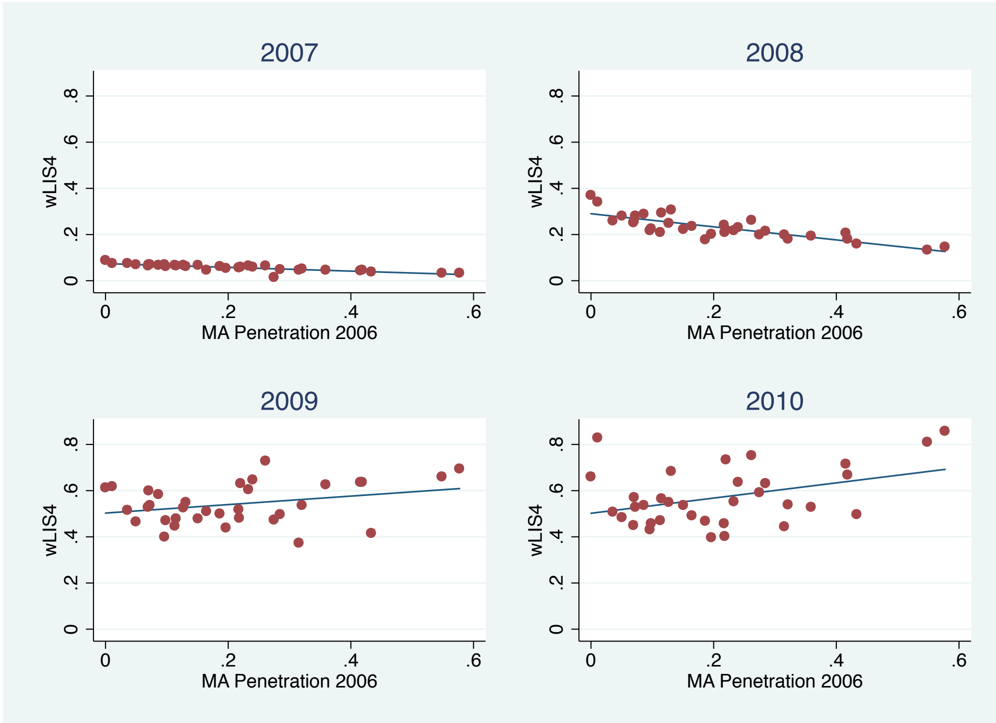
Figure 3: MA-PD Share of Total Enrollment in 2006



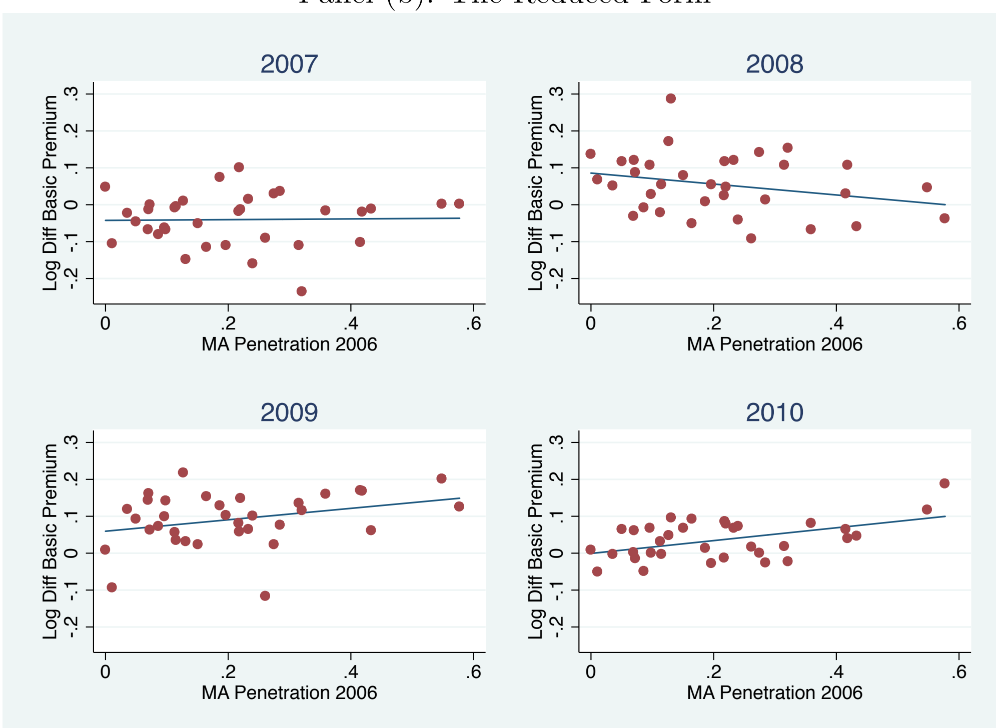
Geographical penetration of the MA-PDs in 2006 across the US States. The distribution of MA-PD Share 2006 is divided into its three tertiles. Darker colors correspond to greater penetration.

Figure 4: 'Visual IV'

Panel (a): The First Stage

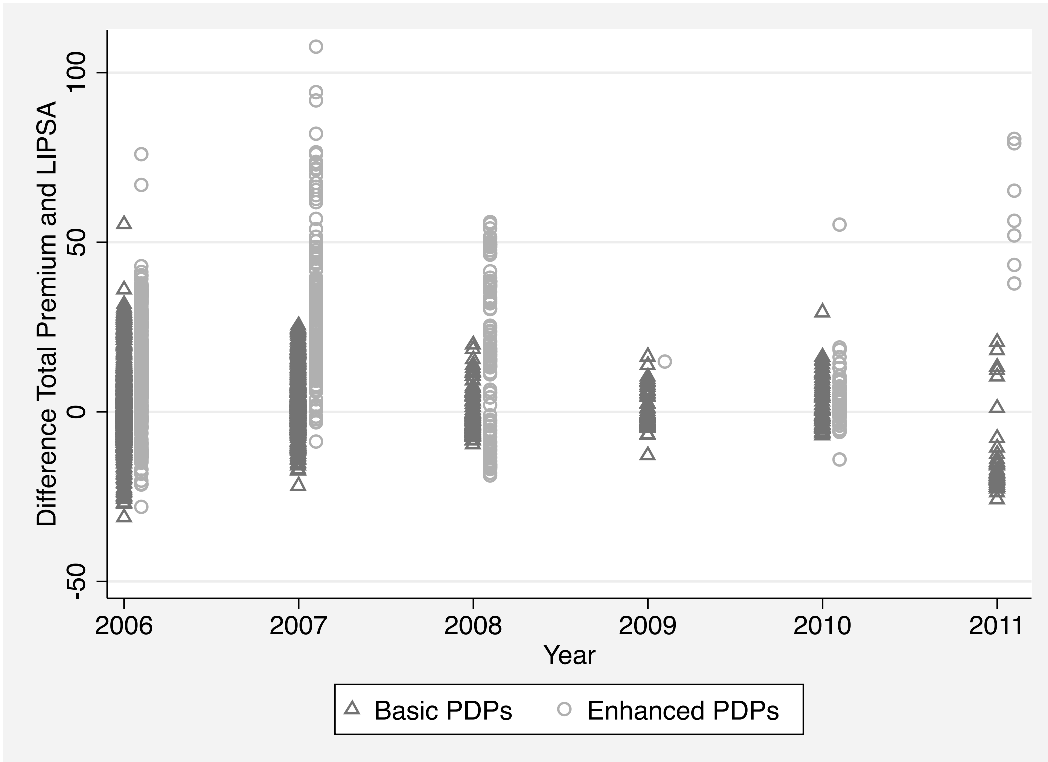


Panel (b): The Reduced Form



Panel (a): Total enrollment share of MA-PDs in 2006 and concentration in LIPSA weights, $wLIS4$. Panel (b): Total enrollment share of MA-PDs in 2006 and log difference in average basic premium, Δ ln($b.premium$). Scatter plots of raw data and OLS regression line (no controls).

Figure 5: First Year Premium of Entering PDPs



Total premium of all the PDPs in the years in which they were introduced.