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

By FRANCESCO DECAROLIS*

This paper shows how in Medicare Part D insurers’ gaming of the subsidy paid to low-income enrollees distorts premiums and raises the program cost. Using plan-level data from the first five years of the program, I find multiple instances of pricing strategy distortions for the largest insurers. Instrumental variable estimates indicate that the changes in a concentration index measuring the manipulability of the subsidy can explain a large share of the premium growth observed between 2006 and 2011. Removing this distortion could reduce the cost of the program without worsening consumer welfare. (JEL G22, H51, I13, I18)

Medicare Part D is the voluntary program that provides insurance for prescription drugs to 26 million Medicare enrollees. In addition to being economically relevant in its own right, Medicare D is also the only example of public insurance delivered exclusively through a choice-based private insurance market. Thus, understanding the functioning of Medicare D serves in assessing the merits of a leading model of health care reform currently debated.

In the policy discussion, not surprisingly, opposite positions have emerged. Advocates of the program stress 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 constant over the first three years (2006–2008), this cost increased by 11 percent per year in the following three years, reaching $55 billion in 2011 (see Table 1).

This rapid cost growth is troublesome because in many respects the design of this innovative market was extremely successful. For instance, reductions in the price of the drugs covered by Medicare D have been shown to originate from the increased

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drug substitutability produced by the use of drug formularies (Duggan and Scott Morton 2010). Nevertheless, this paper shows that a design flaw exists in a key element of this program and that insurers’ exploitation of this flaw can explain a relevant portion of the observed premium increases.

This main design problem that I identify concerns the low income subsidy (LIS) that Medicare pays to enrollees of limited financial resources. About 9 million enrollees (40 percent 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 insurer revenues. The reason this subsidy distorts insurers’ pricing behavior is straightforward if four facts are simultaneously considered. First, about two-thirds 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 the premiums for LIS enrollees in full. Third, the amount of the subsidy is an average of plan 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. As I explain in the first part of the paper, more sophisticated strategies can be used to achieve this result even when insurers offering multiple plans are constrained to offer a single plan of the type targeted to LIS enrollees. 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

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**Table 1—Aggregate Plans Reimbursement Amounts**

<table>
<thead>
<tr>
<th>Year</th>
<th>Enrollees premiums</th>
<th>Direct subsidy</th>
<th>LIS + Copay</th>
<th>Reinsurance</th>
<th>Risk sharing</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006</td>
<td>3.5</td>
<td>17.3</td>
<td>15.1</td>
<td>8.6</td>
<td>-</td>
<td>44.5</td>
</tr>
<tr>
<td>2007</td>
<td>4.1</td>
<td>18.4</td>
<td>16.5</td>
<td>7.1</td>
<td>-0.7</td>
<td>45.4</td>
</tr>
<tr>
<td>2008</td>
<td>5.0</td>
<td>17.5</td>
<td>17.4</td>
<td>6.7</td>
<td>-1.3</td>
<td>45.3</td>
</tr>
<tr>
<td>2009</td>
<td>6.1</td>
<td>18.8</td>
<td>20.3</td>
<td>11.4</td>
<td>-0.1</td>
<td>56.5</td>
</tr>
<tr>
<td>2010</td>
<td>6.7</td>
<td>19.9</td>
<td>20.9</td>
<td>10.5</td>
<td>-0.7</td>
<td>57.3</td>
</tr>
<tr>
<td>2011</td>
<td>7.3</td>
<td>20.1</td>
<td>22.3</td>
<td>12.8</td>
<td>-1.0</td>
<td>61.5</td>
</tr>
</tbody>
</table>

Notes: 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 subsidies for low income enrollees (which include both the LIS, worth of this item, and contributions for drug copayment, worth two-thirds of this item), reinsurance payments (80 percent 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 Trustees of Medicare (2012).

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Table 1 reports the various sources of payments to plans, which are explained in detail in Section II.
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. Using a simple theoretical example, I argue that the current regulation can produce premium distortions. Importantly, these distortions can also affect 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.

To quantify the relevance of this design flaw, I begin the empirical analysis from a descriptive account of a few strategies that insurers might use to game the LIS design. Focusing on the seven largest insurers, I analyze data on plan enrollment and prices between 2006 and 2011. These data seem to offer clear indications that pricing choices respond to the LIS. For instance, I observe that the insurers with the largest shares of LIS enrollees cluster their plan premiums very close to the threshold for the maximum subsidy that Medicare pays for LIS enrollees. This is remarkable since this threshold is not known when insurers submit their premium choices to Medicare. I analyze various other aspects of pricing decisions and, for each of them, find that some insurers appear responsive to the LIS incentives. However, I also find substantial heterogeneity in the insurer behavior both in terms of the extent to which they seem responsive to the LIS and in terms of which pricing strategies they choose. For instance, while a few aspects of CIGNA’s premium choices can be explained as a response to the LIS regulations, this is not the case for Coventry and Humana.

Therefore, in the second part of the empirical analysis I propose a strategy based on market-level premium variations to quantify the economic relevance of premium distortions arising from the insurers’ response to the LIS regulations. In particular, I focus on how the growth in the average premium in the 34 geographical regions into which the United States is divided can be explained by differences in the manipulability of the LIS. Since the LIS is a weighted average of plan premiums, the sum of the four highest weights in a region provides a good measure of LIS manipulability. The analysis uses an instrumental variable approach since the linkage between the weights used to compute the LIS and the changes in the premium would mechanically produce biased ordinary least squares (OLS) estimates. The main findings reveal a clear association between LIS manipulability and premium growth. In particular, the preferred specification indicates an increase of 6.8 percent in premium growth in response to a one standard deviation increase in the concentration of the weights used to determine the LIS. Under an approximation described in the text, this implies that about one-third of the 36 percent nominal growth of basic premiums observed between 2006 and 2011 can be explained by the growth in the concentration of the weights used for the LIS calculation observed in the same period.

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. Second, a recent study by Duggan and Scott Morton (2010) 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 relevant policy implication concerns the need to reform the low income subsidy in Medicare D. This system has been the object of major 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 and Medicaid, their return to a system similar to Medicaid has been proposed. Although this is an effective solution for the problem identified by this paper, another possible solution lies at the opposite end of the spectrum between public and private insurance and consists of using an appropriately designed auction system to allocate LIS consumers to firms willing to compete to offer them insurance. Between these two extremes, a less drastic reform of the current regulation could take three possible forms: (i) diluting the weight that each plan exercises on the calculation of the low income subsidy, (ii) using historical data for its calculation, (iii) setting a fixed amount (or percentage) for this subsidy, and (iv) mandating insurers to offer a single plan. In the last section, I return to these policy suggestions and discuss their relative merits.

Related Literature.—The Medicare D program is described in Duggan, Healy, and Scott Morton (2008). Academic research on this program 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 concluding that many consumers choose suboptimal plans, but that their choices improve as they gain more experience. This paper, by arguing that premiums are distorted, suggests that premiums cannot properly guide consumer choices. Moreover, by offering an explanation for plans proliferation, it addresses a source of the choice complexity problem.

As regards the second issue, Duggan and Scott Morton (2010) have found that plans designed their drug formularies in ways that very effectively increased drug substitutability and limited drug cost increases. In a follow-up study covering the period from 2006 to 2009, Duggan and Scott Morton (2011) confirm the decline in drug costs and argue that premium growth in this period cannot be explained by drug costs. A similar conclusion is reached by Aaron and Frakt (2012). Ericson (2014), instead, offers an explanation of the cost increases based on firms exploiting consumers inertia in plan choice. My analysis contributes to these studies by offering an explanation for premium growth that is complementary to that of Ericson (2014). Moreover, together with Ericson (2014), this paper is the only one directly analyzing the third pillar of Medicare D, competition between plans.

Compared to the previous studies on Medicare D, this paper emphasizes the relevance of the LIS enrollees. LIS enrollees are mostly dual eligibles who are notoriously

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2Heiss, McFadden, and Winter (2007); Abaluck and Gruber (2011); Kling et al. (2012); and Heiss et al. (2013) are among the studies finding evidence of suboptimal plan choices. Ketcham et al. (2012) show that over time consumers rapidly improve their choice of plan.
costly to insure and, because of the Affordable Care Act (ACA), are destined to expand. 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 the Inspector General (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 Morton (1997) and Duggan and Scott Morton (2006), the mandatory rebate induces drug manufacturers 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 for a possible reform.

Finally, this paper contributes to a series of recent studies asking whether a market mechanism could deliver efficient outcomes in health insurance markets. Glazer and McGuire (2009) and Bundorf, Levin, and Mahoney (2012) show how the requirement of a uniform price across consumers distorts prices and allocations. This study focuses on a different source of distortions: the design of public subsidies. Given the use of a similar subsidy design in Medicare C, the results will be relevant for this market too. Moreover, similar mechanisms are used in the Medicare auctions for medical equipment (Cramton, Ellermeyer, and Katzman 2015, and Merlob, Plott, and Zhang 2012). 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 issue.

I. Theoretical Example

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

In any period \( t \), the profits of the firm offering plan \( r \), for \( r \in \{q,j,k\} \), can be written as

\[
\Pi_{r,t} = \left[ p_{r,t} - c^U_{r,t} \right] s^U_{r,t} M^U + \left[ p_{r,t} - c^L_{r,t} \right] s^L_{r,t} M^L \quad \text{for } r \in \{q,j,k\},
\]

where \( M^U \) and \( M^L \) are the total number of unsubsidized and subsidized consumers and \( s^U_{r,t} \) and \( s^L_{r,t} \) are their shares in plan \( r \) in period \( t \). Regulations mandate that the same premium \( p_{r,t} \) applies to all enrollees, thus creating a link between the profits earned on the two types of enrollees. The shares \( s^U_{r,t} \) and \( s^L_{r,t} \) depend on all premiums. In particular, the share \( s^U_{r,t} \) results from unsubsidized enrollees choosing their plan. Thus, under the appropriate assumptions on the utility of unsubsidized enrollees, \( s^U_{r,t} \) will take one of the usual discrete choice problem forms.
The share \( s^L_{r,t} \) behaves very differently. Medicare assigns subsidized consumers to plans based solely on their premium. In particular, Medicare compares each premium to a quantity I will refer to as low income premium subsidy amount (LIPSA) and that, for now, is assumed to be exogenously given.\(^3\) Subsidized enrollees are then allocated to plans with a premium smaller or equal to \( \text{LIPSA}_r \). Thus, \( p_{r,t} > \text{LIPSA}_r \) implies that plan \( r \) cannot enroll subsidized enrollees in \( t \). If such a plan served subsidized enrollees in \( t - 1 \), they are reassigned in equal shares to plans with \( p_{r,t} \leq \text{LIPSA}_r \). These latter plans also retain their subsidized own enrollees from \( t - 1 \). Thus, the plan demand curve is discontinuous: moving down along this curve, the quantity of enrollees jumps up as soon as \( p = \text{LIPSA} \) because for this (and all lower premiums) the plan is assigned a share of subsidized enrollees. Intuitively, for extremely high values of LIPSA, an insurer will set \( p = \text{LIPSA} \), even if only subsidized enrollees enroll at that price. Alternatively, for extremely low values of LIPSA, an insurer optimizes \( p \) considering only regular enrollee demand. For intermediate cases, an insurer might increase or decrease its premium relative to an environment with regular enrollees only. Moreover, premiums will tend to cluster exactly at the LIPSA when facing larger shares of subsidized enrollees and when these enrollees are cheaper to insure. A simple model showing these features is presented in the online Appendix.

More subtle types of distortions, however, occur when the LIPSA is an endogenous function of premiums, as with Part D. Indeed, suppose that the LIPSA is a weighted average of plan premiums, \( \text{LIPSA}_t = \sum_{r \in \{q,j,k\}} w_{r,t} p_{r,t} \), computed using weights that are positive and sum to 1. Clearly, which weights are used to compute \( \text{LIPSA} \), can greatly influence the evolution of market shares. In particular, if the period \( t - 1 \) enrollment shares of subsidized enrollees are used as the weights applied to period \( t \) premiums to calculate \( \text{LIPSA}_t \) (formally: \( w_{r,t} = s^L_{r,t-1} \)), a system I refer to as “enrollment weighting,” then over time there will be a tendency for all subsidized enrollees to converge to a single plan. To see why, suppose that there is an initial period, \( t = 1 \), in which weights are \( w_{q,1} = w_{j,1} = w_{k,1} = \frac{1}{3} \). 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 \( p_k > \text{LIPSA}_1 \) and possibly also \( p_j > \text{LIPSA}_1 \). In the second period either \( \text{LIPSA}_2 = p_q \) or \( \text{LIPSA}_2 = (0.5)p_q + (0.5)p_j \). In both cases \( p_j > \text{LIPSA}_2 \) 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. The system can induce a downward pressure on premiums if firms adjust prices in an attempt to not exceed the LIPSA.\(^4\) 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 to the cheapest plan(s) will happen. On the contrary, no such tendency exists in an “equal weighting” system in which premiums are weighted equally.

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

\(^3\)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.

\(^4\)On the contrary, a firm finding subsidized enrollees too costly might raise its premium above LIPSA.
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. Now the relevant assignment rule of subsidized enrollees for the multiplan firm is as follows: a plan that enrolled subsidized consumers in $t - 1$, but prices above the LIPSA in $t$, loses its subsidized enrollees to reassignment in period $t$ to the other plan of the multiplan firm provided that this plan has a premium at or below the LIPSA in $t$. Hence, the multiplan firm loses all its subsidized enrollees only if in the same period both $p_{q,t} > LIPSA$, and $p_{k,t} > LIPSA$. 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, $q$ also has the lowest cost: $c_j = c_k = 1 > 0.01 = c_q$. 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 one-half to plan $q$ and one-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 their alternation endlessly: 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

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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 higher profits afterward.
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. A simple, but important modification of this example is presented in Section V to explain how the same type of strategy can be implemented under limits to the number and type of plans an insurer can offer.

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 2.5 forever for one-half of the subsidized enrollees while it could have paid 1. Moreover, five other problems arise. First, production is inefficient because one-half of the subsidized consumers remain forever 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 one-half of them forever get high quality and the others low quality for purely random reasons. Fourth, paradoxically the inefficient multiplan firm earns a higher profit per enrollee than the efficient firm. The efficient firm would like to enter with an additional plan to mimic the multiplan firm. Thus, inefficient entry might be another distortion induced by this system. Fifth, the role of the ceiling price (or, as it happens in reality, Medicare assessment of premium reasonableness) is essential as it prevents premiums from exploding.

How could multiplan firms exploit the enrollment weighting system in practice? 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 something remarkably similar to what is done by the multiplan firm in the example through plans consolidation. For Medicare D, the United States 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 in this region and 96 percent of its enrollees were subsidized (13,737 out of 14,310). In 2010, two new plans, one “cheap” ($28.10 premium) and one “expensive” ($34.10), were introduced and the old plan was consolidated into the expensive plan. This meant that CIGNA’s consolidation choice maximized its positive influence on the subsidy (i.e., the LIPSA): its expensive plan had a weight of 8 percent (inherited from the consolidated plan), while its cheap plan had a weight of 0 percent. Once the LIPSA was calculated, the premium of the expensive plan was above the LIPSA and so this plan lost its subsidized enrollees. But none of them were lost by 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 percent lower (holding all other premiums fixed). CIGNA applied this same strategy in 13 other regions that year. Overall, 

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6Finally, competition between multiplan firms does not necessarily help. For instance, adding a second multiplan firm, identical to the first, leaves all the negative features of the example unchanged.
60,846 subsidized enrollees had to be moved out of CIGNA plans because of Medicare-mandated reassignment due to 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.

II. Market Regulation

The regulation of Medicare Part D is complex and has evolved 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 United States into 34 geographic 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, deductible, co-insurance/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 also covering additional drugs outside the Medicare list (enhanced plans). The premium of enhanced plans is divided into two components, basic and enhanced, and Medicare subsidies can only be used 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). For 2006, the MA-PD share varies widely, ranging from almost 60 percent in Arizona and Nevada to less than 4 percent in Mississippi and Maine. This different geographic penetration in 2006, clearly shown in Figure 2, is predominantly driven by various state mandates that, starting in the early 1990s, fostered enrollment into Medicare Managed Care (MMC) plans, part of the Medicare Advantage system. In Section VI, I will use this fact to develop an instrumental variable strategy.

Similarly, distinguishing between the two groups of enrollees is useful. Medicare beneficiaries with limited financial resources are entitled to a low income subsidy (LIS). I will refer to these individuals as LIS enrollees and to the remaining individuals as regular enrollees. As reported in Table 2, LIS enrollees compose about 40 percent of all the enrollees. Both regular and LIS enrollees receive a subsidy to pay their premium called the “direct subsidy.” LIS enrollees also receive an additional subsidy to pay for the premium and discounts for certain expenditures

7 The Medicare Advantage system introduced in 2003 replaced the forerunner Medicare C. Both the old and the new systems consisted of a market for private health insurance plans that offered Medicare enrollees the benefits of the original Medicare plan. However, Medicare Advantage plans were meant to be more attractive to consumers because they were also allowed to offer coverage for prescription drugs.


9 In 2009, Medicare beneficiaries with limited resources ($12,510/individual; $25,010/couple) and income below 150 percent 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.
not covered by plans. These subsidies are paid directly by CMS to insurers and, as discussed below, they represent a key component of plans revenues.

A. 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 percent of the total reimbursements. Medicare payments can be divided into four categories: (i) direct subsidy, which is paid for every consumer enrolled and is identical for all

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**Table 2—Number of Enrollees by Type of Enrollee**

<table>
<thead>
<tr>
<th>Year</th>
<th>Total enrollment</th>
<th>LIS enrollment</th>
<th>Reassigned</th>
<th>Auto-enrolled</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Total LIS PDPs</td>
<td>Total reass. Prem. raise</td>
<td>Auto-enrolled Choosers PDPs</td>
</tr>
<tr>
<td>2006</td>
<td>20,514,830</td>
<td>0.42 0.39</td>
<td>— —</td>
<td>0.38 0.02</td>
</tr>
<tr>
<td>2007</td>
<td>21,856,800</td>
<td>0.40 0.37</td>
<td>0.10 0.10</td>
<td>0.35 0.02</td>
</tr>
<tr>
<td>2008</td>
<td>23,100,694</td>
<td>0.39 0.35</td>
<td>0.07 0.06</td>
<td>0.27 0.07</td>
</tr>
<tr>
<td>2009</td>
<td>24,094,520</td>
<td>0.37 0.33</td>
<td>0.05 0.05</td>
<td>0.24 0.08</td>
</tr>
<tr>
<td>2010</td>
<td>25,040,622</td>
<td>0.37 0.32</td>
<td>0.04 0.03</td>
<td>0.25 0.07</td>
</tr>
<tr>
<td>2011</td>
<td>25,877,644</td>
<td>0.37 0.32</td>
<td>0.03 0.03</td>
<td>0.28 0.04</td>
</tr>
</tbody>
</table>

Notes: Total enrollment, in the second column, is calculated using PDPs and MA-PDs as specified in the note to Table 4. The following columns are expressed as shares of the total enrollment. The LIS enrollment is reported both across all plans and only within PDPs. The column “Total Reass.” indicates the LIS enrollees that CMS reports to have reassigned in that year. The following column indicates the LIS enrollees that were reassigned because of plans losing eligibility due to a premium above the LIPSA. All other reassignments are due to plan terminations, which imply that both choosers and auto-enrolled LIS enrollees in the terminating plans were randomly reassigned. The last two columns divide the LIS enrollees between auto-enrolled and choosers (in PDPs; the remaining choosers are in MA-PDs and their share can be calculated by subtracting the sum of the last two columns from the value of the total LIS enrollment in the third column). CMS does not disclose the number of choosers (or auto-enrolled). I calculate the number of chooser as the number of LIS enrollees either in MA-PDs or in non-eligible (because of premium or enhanced type) PDPs. A different calculation method used in Summer, Hoadley, and Hargrave (2010) produces qualitatively similar results.
enrollees up to an adjustment for their risk score; (ii) low income subsidy, which is a contribution for consumers of limited financial resources; (iii) individual reinsurance, which consists of the payment of 80 percent of drug spending above a certain value known as the catastrophic threshold; (iv) risk corridor payments that ensure that the profits/losses made by the sponsor are within certain bounds.

The amount of both the direct and low income subsidies depends on prices set by insurers. Specifically, 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, 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 1 (in 2012, it was 0.63). The plan premium that an enrollee will see on the CMS website is the difference between the plan bid and this direct subsidy. Thus, some plans can have a premium of zero dollars. In turn, premiums are used to calculate the low income subsidy.

B. LIPSA Calculation

CMS determines the additional subsidy for LIS enrollees separately for each of the 34 US regions. The dollar amount of this subsidy, known as the low income premium subsidy amount (LIPSA), is calculated as follows: for a given region, the LIPSA is the weighted average of (the basic component of) plan premiums. However, contrary to the direct subsidy where weights are based on previous-year total enrollment, since 2009 the weights are based only on previous-year enrollment of LIS beneficiaries when calculating the LIPSA. Prior to 2009, the system operated very differently with plans weighted (almost) equally in the calculation of the LIPSA.

More precisely, before 2009 all the PDPs within the same region were weighted equally and their cumulative weight had to be equal to the share of total enrollment in PDPs in the region. Thus, high MA-PD enrollment meant a low weight for each PDP. The 2009 switch to enrollment weighting caused a reversal in this relationship between weights and the MA-PD penetration. Regions with a high MA-PD penetration had registered low LIPSA values in the first years because the near-zero premiums of most MA-PDs had lowered the amount of the subsidy. This necessarily implied that only a 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. This reversal will play a key role in my instrumental variables strategy.

11 Even more precisely, the details of how the LIPSA is calculated have changed over time: (i) 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; (ii) for 2008, a weighted method was used in which 50 percent of the weight was assigned with the same method of 2006 and 2007 and the remaining 50 percent was assigned to a weighted average of PDP and MA-PD bids with weights proportional to total enrollment (in the previous year); (iii) 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); (iv) 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.
As shown by Table 1, the switch to enrollment weighting occurred contemporaneously with a substantial increase of the LIS reimbursements, amounting to $3.1 billion. Indeed, the new weighting method reduced the weights of MA-PDs, that typically have both low premiums and few LIS enrollees, and increased that of PDPs, that typically are relatively more expensive and enroll more LIS enrollees. Thus, a first reason for the higher LIS reimbursements is that, even if 2009 premiums had been identical to 2008, the reassignment of LIPSA weights would have mechanically increased the LIPSA implying that relatively more expensive plans would have experienced both greater LIS enrollment and larger LIS payments. In addition to this “mechanical effect,” the strategic manipulation of the LIS threshold that I analyze below also contributed to the shift of LIS enrollees into relatively more expensive plans. As regards the effects of this reform on the LIPSA weights, this is further described in Table 3 which reveals both the marked increase in the LIPSA weights concentration after 2008 and the greater concentration of the LIPSA weights relative to the national average weights. These latter weights (reported in the first block of Table 3) are on average 0.045 percent and, of all the 8,070 PDPs, only 8 plans have a weight above 1 percent. In contrast, the LIPSA weights (second and third blocks of Table 3) are often greater than 1 percent and, after 2008, the highest fifth percentile has a weight above 20 percent, with a maximum of 63.99 percent.

C. Random Reassignment

While regular enrollees choose their plan in fall of the year before the coverage starts, LIS enrollees typically do not choose their plan but are assigned to it. For 2006, CMS performed this task for each region by allocating at random LIS enrollees across firms that had at least one basic PDP with a premium at or below the LIPSA. 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, if this plan 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 (i) maintain their status of full LIS receivers and (ii) 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 (ii) are referred to as “choosers.” Opting out to choose a plan can be done at any time during the year. For choosers, CMS sends a letter every year to remind them that they need to act on their own to avoid paying a positive premium, but no automatic reassignment occurs.

The enrollment figures in Table 2 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 reassignment. The number of those enrollees for which the random reassignment occurs varies substantially from year to year.

12 For a plan to qualify for the randomly assigned beneficiaries, its premium had to be at or below LIPSA and it had to be a PDP with a benefit type designed as standard benefit or actuarially equivalent. The latter requirement on benefit types is not enforced in subsequent years and I will ignore it in the rest of the paper. 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.
ranging from 0.9 million to 2.1 million reassignments.\textsuperscript{13} With the ACA expanding the number of enrollees eligible for the LIS, and since LIS choosers return to random reassignment upon plan termination,\textsuperscript{14} reassignments will potentially remain a major feature of this market. Furthermore, as the example of CIGNA in Section II revealed, random reassignments often occur within plans of the same insurer. For 2010, CMS disclosed its estimate for the proportion of within-insurer reassignments: for this year, 89,324 enrollees (8 percent of all reassignments) were

\begin{table}[h]
\centering
\begin{tabular}{llllllllll}
\hline
 & \multicolumn{2}{c}{National weights} & \multicolumn{2}{c}{LIPSA weights 2007–2008} & \multicolumn{2}{c}{LIPSA weights 2009–2011} \\
 & Full sample & \geq 1 percent & Full sample & \geq 1 percent & Full sample & \geq 1 percent \\
\hline
Panel A. Weights of all PDPs, 2007–2011 & & & & & & \\
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 \\
Observations & 8,062 & 8 & 3.690 & 2.413 & 4.372 & 1.365 \\
\hline
Panel B. Top eight cumulative weights of plan sponsors, 2007–2011 & & & & & & \\
Year & Weight & Region & Year & Region & Weight & Region & Weight \\
2nd & 2011 & 1.222 & 2008-AK & 18.038 & 2011-HI & 52.369 \\
4th & 2011 & 1.147 & 2008-DE,DC,MD & 12.800 & 2011-MO & 44.032 \\
8th & 2009 & 1.014 & 2008-IN,KY & 10.620 & 2010-NH,ME & 38.830 \\
\hline
Panel C. Top eight cumulative weights of plan sponsors, 2007–2011 & & & & & & \\
Firm year & Weight & Region & Firm year region & Weight & Firm year region & Weight \\
1st & 2010 & 24.7 & UHG 2008-AZ & 33.2 & Coventry 2010-NV & 64.7 \\
2nd & 2011 & 24.4 & UHG 2008-CO & 30.9 & UHG 2011-HI & 52.4 \\
3rd & 2009 & 23.4 & UHG 2007-CO & 30.4 & UHG 2011-NH,ME & 51.0 \\
4th & 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 \\
\hline
\end{tabular}
\caption{Weights of the PDPs}
\end{table}

Notes: 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 percent 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.

\textsuperscript{13} The number of reassignments is higher in 2006–2008 than in 2009–2011. The gradual market stabilization, indicated by a lower variance in the number of insurers and their increased specialization in the LIS or regular enrollee markets partially explains the decrease. The major increase in the LIPSA above 2008 levels likely depressed reassignments further in 2009–2010, as did the de minimis policy in 2011.

\textsuperscript{14} Plan terminations are rather common. In 2010, 17 percent of all reassignments (200,000 enrollees) involved former choosers that returned to random reassignment because their plans were terminated.
to occur within the same insurer. CIGNA, CVS Caremark, Coventry, and Universal American all received within-firm reassignments.\footnote{Although CMS estimates are unavailable for other years, an estimate of the frequency of within-firm reassignments can be obtained by comparing the maximum potential number of LIS enrollees that an insurer releases toward random reassignment ($L\text{IS}^-$) to a proxy for number of potentially randomly reassigned LIS that it gains in the same market ($L\text{IS}^+$). A within-firm reassignment is likely when $L\text{IS}^+ \geq L\text{IS}^- > 0$. In the data, conditioning on the 4,480 cases where $L\text{IS}^- > 0$, 21 percent of the times $L\text{IS}^+ \geq L\text{IS}^-$. Moreover, in 38 percent of these cases $L\text{IS}^+ > 0$.} Table 4 reports in the bottom-right portion of panel B the number of basic PDPs of each one of the seven largest insurers. A value larger than 34 necessarily implies that the same insurer is offering multiple plans within the same region/year that might allow it to receive a within-firm reassignment. The lower values observed for 2011 are due to a change in regulation known as meaningful difference aimed at restricting firms to offer at most a single basic and two enhanced PDPs per region, and to have a minimum premium difference between each of these plans. In the following years, however, firms rapidly adjusted to this reform by increasing the number of brands under which they market their plans since these limits apply at brand level.\footnote{For instance, after CVS completed the acquisition of Longs Drug Stores (LDS) in October 2008, in the following years it continued to offer both CVS plans (branded as SilverScript) and LDS plans (branded as RxAmerica). Indeed, this is why panel B of Table 4 reports that CVS offered 68 basic PDPs in 2011, despite the meaningful difference regulation. Similarly, although CIGNA had completed its acquisition of Health Spring by January 2012, it offered its basic PDPs under the two brands: in each region in 2013 basic PDPs where offered under both CIGNA Medicare Rx and HealthSpring Prescription brands.}

One last important regulation is a de minimis policy that CMS introduced in 2007 and 2008 (on a provisional basis) and from 2011 onward (on a permanent basis) to limit the reassignment of LIS enrollees.\footnote{While the reassignment process was designed to limit the risk that LIS individuals would have to pay a premium, it might harm their continuity of coverage. For this reason, six states went even further and introduced some limitations to the role of random reassignments through forms of “beneficiary-centered” assignment. However, only Maine essentially replaced the CMS system and matched LIS enrollees to plans based on drug consumption. The other five states, instead, provided the randomly assigned LIS enrollees with detailed information about plans to which they could transfer for better match their drug needs.} This policy provides the opportunity for those plans with premiums above the LIPSA by just a small amount to retain their LIS enrollees by lowering the premium to the LIPSA for only their LIS enrollees. For the option to apply, the maximum amount by which the premium could be greater than the LIPSA was set to $1 in 2008 and $2 in all the other years. For instance, in 2011 a plan with a premium within $2 above the LIPSA could decide to keep its LIS beneficiaries by accepting to get reimbursed by Medicare at a premium equal to the LIPSA. This policy is particularly relevant because it allows us to observe that essentially all insurers facing the choice of applying the de minimis discount to retain their LIS enrollees opted to do so.

Finally, before starting the empirical analysis, it is worth stressing three additional elements of evidence that LIS enrollees are profitable for insurers. The first is the simple observation that these enrollees do not require the same type of marketing expenditure that regular enrollees do. Second, among the various mergers and acquisitions that occurred in the market, two involved CVS purchasing plans that were almost exclusively enrolling LIS enrollees. Given the price paid for these acquisitions, back of the envelope calculations suggest that LIS enrollees have a value in line with that of regular enrollees.\footnote{The two acquisitions that CVS completed during the sample period both involved companies highly concentrated in LIS enrollees. For LDS, 84 percent of its enrollees in 2008 were LIS receivers. The second acquisition involved the whole set of Universal American PDPs. When it was completed (April 2011) out of the 1.88 million enrollees in Universal American PDPs, 1.43 million were LIS receivers. Given a price paid of $1.25 billion, a} The third element is that monthly
plan bids appear to be enough to fully cover the average drug expenditures per LIS enrollees that are recorded in the CMS microdata. These elements suggest that

back-of-the-envelope calculation suggests that the net present value of a LIS beneficiary is about $660. This value is in line with the price per consumer paid in other mergers involving companies with mostly regular enrollees and supports the idea that insurers value LIS enrollees.

In particular, for the years 2007, 2008, and 2009, given that plans on average face average monthly drug payments of $102, $104, and $114 per LIS enrollees, and given that the Congressional Budget Office estimates an
insurers prefer to enroll LIS receivers, despite, as argued by Hsu et al. (2010), their risk adjustment being insufficient. Gaming of the LIS can explain why this occurs.

III. Data

This study uses publicly available data released by CMS describing enrollment and plan features for all plans offered between 2006 and 2011 (CMS 2006–2011, see links to the data files in the online Appendix). I use these data at two different levels of aggregation: plan-level and market-level (where the market is a region/year combination).

A. Plan-Level Data

In panel A of Table 4, I report plan summary statistics distinguishing between PDPs (separately for basic and enhanced plans) and MA-PDs. These plan-level data allow us to observe enrollment (separately for regular and LIS enrollees) and several other plan characteristics. The main ones are: the basic and enhanced components of the premium, the type of PDP and MA plan, the deductible, the type of coverage in the gap, the identity of the insurer, the drug formulary, and the pharmacy network. The statistics in the table reveal that the average total premium is lowest in MA-PD plans, followed by basic PDPs, and then by enhanced PDPs. The data also indicate that LIS enrollees are particularly concentrated in basic PDPs. Finally, the number of plans appears to be large for each category of plans.

In the plan-level data, 276 distinct insurers appear at least once. However, by looking at total enrollment into PDPs in 2011, only seven firms have a market share of at least 3 percent. They are: United Health, Humana, Universal American, CVS Caremark, Coventry, WellCare, and CIGNA (in decreasing order of enrollment share). In panel B of Table 4, for each firm I report data on enrollment and number of PDPs offered. As regards enrollment, the top-left panel shows the total enrollment share into PDPs and its evolution from 2006 to 2011. Several firms like CIGNA, Universal American, and CVS Caremark experienced a remarkable growth in this period. The panel on the top-right shows that these same three firms are also the ones that in 2011 have the largest ratio of LIS enrollees to total enrollees (across all their plans, PDPs, and MA-PDs): for all of them the share of LIS enrollees over total enrollees is above 70 percent. This share exhibits large fluctuations and, while for CIGNA it increases from 57 percent to 71 percent from 2006 to 2011, for Humana, WellCare, and Coventry it declines by more than 10 percentage points in the same period. The bottom-left and bottom-right panels report the number of PDPs and basic PDPs offered, respectively. Reasons for the variation over time in these numbers were discussed in the previous section.
B. Market-Level Data

The dataset for the main empirical analysis is aggregated at the region and year level because this analysis concerns 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. 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 \( b_{premi} \), 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 \( \Delta \ln(b_{premi}) \). Panel C of Table 4 reports some summary statistics for \( b_{premi} \).

The main independent variable seeks to capture both how lucrative and how easy it is to manipulate the LIPSA in a market. Thus, I use a variable that equals the sum of the four 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.\(^{21}\) This variable has a mean of 41.5 percent and ranges from its lowest value of 0.03 in 2007 in both region 28 (AZ) and 29 (NV), to a maximum of 0.93 in 2011 in region 1 (NH, ME). Interestingly, the second highest value in the sample, 0.89, belongs 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 calculation changed over time (see Section III). In Section V, 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 (HHI) 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 ingredients covered (relative to all active ingredients covered by Medicare for the year). As discussed later, the first variable is useful in controlling for switching costs, while the latter two serve to control for changes in the mean plan generosity.

IV. Plan-Level Descriptive Analysis

In this section I will use the plan-level data to analyze whether insurer choices are indicative of LIS distortions. Since the market is characterized by a large number of heterogeneous firms, each with a broad collection of possible actions, I will focus primarily on the seven largest insurers and analyze only a few of their possible

\(^{21}\) Indeed, \( wLIS4 \) seems a better proxy for the likelihood of LIS manipulations relative to, for instance, the sum of the LIPSA weights of the four 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.
actions. In particular, I begin by describing how the LIS appears to distort the entire distribution of premiums, regardless of whether this happens through firms actively trying to manipulate the LIPSA. Then, I present evidence suggestive of the presence of active manipulations.

**Clustering at the LIPSA.**—Figure 3 reports four histograms that illustrate premiums concentration at the LIPSA. Panel A reports the difference between plan premium and the low income subsidy amount. Panels B and D show the histograms of the same variable, but exclusively for PDP. These two histograms weight plans by their enrollment: LIS enrollment for panel B and non-LIS enrollment for panel D. Panel C is the histogram of the difference between the plan premium and the cheapest basic PDP premium in the region and is reported for eligible PDP weighted by their LIS enrollment.

**Notes:** Panel A shows for all plans (PDP and MA-PD) the histogram of the difference between the plan premium and the LIS amount. Panels B and D show the histograms of the same variable, but exclusively for PDP. These two histograms weight plans by their enrollment: LIS enrollment for panel B and non-LIS enrollment for panel D. Panel C is the histogram of the difference between the plan premium and the cheapest basic PDP premium in the region and is reported for eligible PDP weighted by their LIS enrollment.
readjusted over time to be right at the LIPSA, random reassignment together with
the enrollment-weighted LIPSA would mechanically lead to the convergence of LIS
enrollees to the cheapest basic PDP in their region. Finally, panel D shows the differ-
ence between premiums and the LIPSA, weighting plans by their non-LIS enrollees.
The LIPSA value influences the premiums of regular enrollees too, since most of
them enroll in plans whose premium is remarkably close to the LIPSA.

The top three panels in Figure 4 complement the previous histograms by show-
ing that over time there is no increased convergence to the cheapest PDPs. Each
panel reports on the vertical axis the difference between basic PDP premiums and
the LIPSA, and on the horizontal axis the total LIPSA weight of the insurer in the
region and year. Absent manipulations, enrollment weighting would have elimi-
nated “empty” low-premium plans, leaving no dots in the left corner of each panel
lying below the LIPSA. On the contrary, the data reveal that the frequency of plans
that have both a low weight and a premium substantially lower ($20 and more) than
the LIPSA grows over time.

A second interesting pattern revealed by the bottom three panels in Figure 4 is
the heterogeneity across insurers. The tendency to cluster premiums at the LIPSA
is present for some, but not all insurers. Universal American (panel D) and CIGNA
(panel E) appear to place all their plans with a high LIS share very close to the
LIPSA (and within the $2 de minimis amount). A similar pattern is observed for
United Health, CVS, and WellCare. In contrast, Humana (panel F) and Coventry
premiums appear not to respond to the LIPSA. Since any difference between the
LIPSA and the premium of an eligible PDP is essentially money left on the table,

\[ \text{I include only regions with at least four eligible PDPs, to avoid situations in which the difference between the premium and the LIPSA is zero because all LIS enrollees have converged into the cheapest PDP.} \]
this comparison suggests that either there is learning with Humana being less sophisticated than Universal and CIGNA, or that Humana pursues different goals. Similarly, substantial heterogeneity emerges when comparing the premium at which insurers launch their new PDPs. Figure 5 shows the difference between plan premiums and the LIPSA for the year in which the plans were introduced (excluding 2006). The figure separates basic and enhanced PDPs because only the former should respond to the LIPSA. Figure 5 reveals that United Health did not launch new plans, while CVS did not introduce basic PDPs. The remaining five firms used this capability, but in different ways: Universal American, CIGNA, and WellCare priced their basic PDPs close to the LIPSA. Humana and Coventry, instead, do not seem to be responsive to this type of incentive.

Clustering at the LIPSA is suggestive of distortions, but not necessarily of subsidy manipulations. The next results look at how plans evolve through time in terms of both premiums and basic/enhanced type to provide some more direct evidence of manipulations.

Discontinuous Premium Increases and Decreases.—I begin by analyzing correlations between premium changes and plan LIS enrollment. Indicating $\Delta p_{ijt}$ as the premium percentage change between $t - 1$ and $t$ for plan $i$ in region $j$ and $\text{Share}_{ijt-1}$ as the share of this plan’s LIS enrollees relative to its total enrollees in year $t - 1$, Table 5 reports the correlation of $\Delta p_{ijt}$ and $\text{Share}_{ijt-1}$ conditional on $\text{Share}_{ijt}$ and other controls. The first column pools together all PDPs and reports a negative correlation between lagged LIS enrollment and premium growth. To explore this correlation more

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23 In support of the latter explanation, Ericson (2014) reports how Humana explicitly stated that its goal was to target regular enrollees through cheap plans. However, the learning explanation is plausible too given that firms bid simultaneously without knowledge of the rival bids.

24 Insurers have at least two other ways to introduce new basic plans: by switching enhanced plans to basic and by merging with other insurers but preserving both product lines. CIGNA and CVS, respectively, seem to use both strategies as mentioned in the text where these strategies are described.
systematically, the next columns split the PDP sample into partitions that should capture plans facing different incentives to manipulate the subsidy. The second and third columns partition the sample between PDPs with a LIPSA weight above or below the average. The last two columns partition the PDP sample into those eligible at $t - 1$ and those not. Indeed, comparing the first three columns, we observe that the sign of both LIS share coefficients flips between the two subgroups used for column 2 (the plans with a LIPSA weight above average) and column 3 (the other plans). The signs in column 2 are what one would expect if high weight plans were used to increase the LIPSA: high weight plans with a large LIS share in $t - 1$ increase their premiums, losing LIS enrollees in $t$. Moreover, column 3 is compatible with downward pressure on premiums from the LIPSA: low weight plans, incapable of manipulations but with a high LIS share in $t - 1$, lower premiums to avoid losing LIS enrollees, thus benefiting LIS enrollment in $t$. A similar, albeit less clear pattern is revealed by the alternative partition in columns 4 and 5.

The theoretical example in Section II, however, suggests that a more direct way to look for potential manipulations is to study drastic premium changes. Hence, I create dummy variables to indicate which premium changes qualify as "jumps." I consider two cases: first, a dummy equal to 1 when the premium increases more than 75 percent; second, a dummy equal to 1 when the decrease is more than 40 percent. The probit model estimated is

$$
Pr(Premium\_Jump_{ijt}) = \Phi(\alpha + \beta_1(wLIS\_Firm_{ijt}) + \beta_2(Eligible\_Firm_{ijt})
+ \beta_3(wLIS\_Firm_{ijt}) \times (Eligible\_Firm_{ijt})
+ \gamma X_{ijt} + \tau_t + \lambda_j + f_i),
$$

where $i$ indexes the plan, $j$ the region, and $t$ the year. $Premium\_Jump_{ijt}$ is one of the two dummy variables and $\Phi$ is the CDF of the unit-normal distribution. Two independent variables are particularly relevant: 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, $\beta_1$...
should be positive when the dependent variable is a positive jump and negative for negative jumps. The second variable is Eligible_Firm, that is a dummy equal to 1 when the insurer offers multiple basic plans in the market, and plan i is not the plan with the lowest weight for the firm. Thus, this dummy captures those plans that should experience a jump up according to the argument in the theoretical example. However, increasing the subsidy is feasible only for firms that have sufficiently high weight. Hence, the main coefficient of interest is $\beta_3$, the effect of the interaction of the two previously described variables. The regressions also include dummy variables to control for years, $\tau_t$, regions, $\lambda_j$, and the identity of the 15 largest firms, $f_i$. The matrix $X_{ijt}$ contains additional covariates and differs across the specifications analyzed.

Table 6 reports the conditional correlations for six probit models, three for each one of the two dependent variables. For positive jumps, the estimates of the marginal effects of the interaction term are positive and strongly significant across the three specifications. Relative to model 1, model 2 includes SoloBasicPDP. 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, the fact that the sign of the estimates coefficient is negative for positive jumps and positive for negative jumps suggests that insurers actively try to increase their share of LIS enrollees. Including in models 3 and 6 controls for the plan age, the share of active ingredients covered and the number of in-network pharmacies does not alter these results.

Table 6—Probability of Large Premium Changes

<table>
<thead>
<tr>
<th></th>
<th>Increase &gt; 75 percent</th>
<th>Decrease &gt; −40 percent</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>wLIS_Firm</td>
<td>0.089*** (0.033)</td>
<td>0.078** (0.033)</td>
</tr>
<tr>
<td>LIS eligible firm</td>
<td>−0.004 (0.009)</td>
<td>−0.008 (0.017)</td>
</tr>
<tr>
<td>(wLIS_Firm)*</td>
<td>0.183*** (0.067)</td>
<td>0.183*** (0.065)</td>
</tr>
<tr>
<td>(LIS eligible firm)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Solo basic PDP</td>
<td>−0.021*** (0.005)</td>
<td>−0.020*** (0.005)</td>
</tr>
<tr>
<td>Other controls</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>5,664 (5,664)</td>
<td>5,664 (5,664)</td>
</tr>
</tbody>
</table>

Notes: Sample: PDPs only. Marginal effects estimated through a probit regression. All regressions include dummy variables for region, year, enhanced plan, year the plan was introduced, and identity of the 15 largest firms. Columns 3 and 6 include also controls for pharmacy network size, share of active ingredients covered, and plan age. 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.

*** Significant at the 1 percent level.
**  Significant at the 5 percent level.
*   Significant at the 10 percent level.

Changes between Enhanced and Basic Type.—One difficulty in identifying LIS manipulations by looking at plans prices over time is that insurers frequently close plans and open new ones. Moreover, they can switch their status between basic and enhanced (20 percent of all PDPs in the market experience at least one switch...
between 2006 and 2011). In Section II, one of the two basic plans offered by CIGNA in 2010 was a plan converted from enhanced into basic. This strategy is particularly important for LIS manipulations by single-brand insurers under the 2011 meaningful difference rule, which restricts these firms to offer at most one basic and two enhanced plans. A simple modification of the example in Section II is to expand the set of actions to include switching plan type. This allows the multiplan insurer to achieve the same equilibrium described in the example despite offering one basic plan only. Interestingly, in 2013 United Healthcare behaved in a similar way in 30 regions: it switched all the basic plans it offered in 2012 (that enrolled about 4 million people in total, 0.9 million being LIS receivers) into enhanced plans and increased their premiums, while at the same time in all these regions it introduced new basic plans at a lower price.

Insurers’ heterogeneity across the different strategies analyzed suggests a coarse classification of firms based on their responsiveness to the incentives created by the LIS: Coventry and Humana do not take actions to gain from the LIS design, while the remaining five firms do so to some extent. Other elements of the plan design point to a similar classification. For instance, Abaluck and Gruber (2011) show that regular enrollees highly value a low deductible. Thus, insurers interested in regular enrollees should opt for a low deductible. This is exactly the strategy adopted by Coventry in every year after 2006, but is the opposite of what is done by Universal, CVS, and CIGNA. Overall, the evidence in this section suggests that over time premiums are likely to grow in response to the greater concentration of LIS enrollees into those insurers most interested in exploiting the LIS design. Moreover, premium growth could result from insurers’ learning how to better game the system. However, the great variety of possible strategies and the heterogeneity across firms in their usage make it difficult to quantify their overall impact. Thus, given the centrality of program cost in the discussion over Part D, in the next section I propose an empirical strategy using market-level data to quantify the effects of LIS distortions on premium growth.

V. Market-Level Empirical Analysis

A. Empirical Strategy

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

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

The coefficient of interest is \( \beta \). A positive and significant coefficient for \( \beta \) would support the hypothesis that greater manipulability of LIS weights is associated with a faster growth in premiums. In an ideal environment, we would observe different levels of \( wLIS4 \) assigned randomly to otherwise identical markets. What is

\[ ^{25} \text{Specifically, the basic plan that in } t - 1 \text{ enrolls LIS enrollees is converted to enhanced in } t \text{ and its premium is set to 4. The other plan that was enhanced in } t - 1 \text{ is converted to basic in } t \text{ and its premium is set at 2.5.} \]
observed in the CMS dataset differs from this and, hence, the empirical strategy proposed tries to correct for departures from this ideal. 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, Duggan, and Ramanarayanan (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 poses particular concerns with the interpretation of the estimates because, after the switch to enrollment weighting in 2009, both \( \omega_{LIS4,jt} \) and \( HHI_{t-1} \) depend on the enrollment concentration at \( t - 1 \).

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 ingredients 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 (as argued in Ericson 2014). All regressions include year and region fixed effects to control for unobserved characteristics. Finally, I present all regression models both with and without region-specific time trends.

The second element of the empirical strategy follows an instrumental variables approach for the identification of \( \beta \). In addition to the usual concerns about omitted variables, the presence of a bias in the OLS estimate of \( \beta \) is due to the mechanical relationship between the average premium and the LIPSA weight concentration. To see this, suppose all LIS enrollees are subject to random reassignment and consider the case of a region where plans have different premiums, but these premiums remain fixed over time. If at time \( t - 1 \) all plans have the same LIPSA weight, some of them must turn out to be above \( LIPSA_{t-1} \). These plans lose their LIS enrollees in \( t - 1 \) and, hence, will have a zero weight in subsequent periods. The weight they had in the calculation of \( LIPSA_{t-1} \) is redistributed in \( t \) to the plans that in \( t - 1 \) are at or below \( LIPSA_{t-1} \). Thus, the measure of weight concentration, \( w_{LIS4} \), increases between \( t - 1 \) and \( t \). Over these two periods, however, the average premium, \( \delta_{premium} \), declines because of the reassignment of LIS enrollees toward cheaper plans. This mechanical comovement of average premiums and weights concentration creates a bias in the regression of premium growth on the weight concentration. Although the sign of the bias is ambiguous, its presence suggests the need for an instrument.

The instrument that I use to correct for this bias is the product of the MA-PD share in 2006 with a dummy equal to 1 from 2009 onward and zero in the previous years. This variable satisfies the exogeneity and correlation conditions for a valid instrument. The exogenous nature of the instrument is supported by the fact that the 2009 reform occurred on a national basis. Moreover, as argued in Section II, the asymmetric penetration of MA-PDs in 2006 is mostly driven by the different evolutions of Medicare C mandates across states. Thus, it seems reasonable to argue that the MA-PDs penetration in 2006 is exogenously determined relative to the main relationship between LIPSA weights and the premium growth that I seek to study, especially after controlling for market fixed effects and time trends.
Panel A of Figure 6 graphically shows the relationship between the MA-PD share in 2006 and \( \text{wLIS}_4 \) separately for each year 2007–2010. Three facts emerge clearly: the strong linear correlation present in each year, the inversion of the sign in 2009 and, crucially, the persistence of a negative relationship in 2007 and 2008 followed by a positive relationship in 2009 and 2010. These facts suggest the presence of a powerful first-stage relationship between \( \text{wLIS}_4 \) and the instrument. Furthermore, for the reduced-form relationship panel B of Figure 6 shows patterns identical to those documented for the first stage: the sign of the relationship flips in 2009; this is not driven by preexisting trends. Since no other regulatory changes concerned Medicare D in 2009, the change in the relationship between premium growth and the instrument is likely to be driven by the change in \( \text{wLIS}_4 \).

To better quantify the first-stage relationship, the box at the top of Table 7 reports OLS regressions of \( \text{wLIS}_4 \) on the instrument for six specifications. The models in the first two columns include region and year fixed effects, while the following columns add controls for market and plan characteristics. The specifications in the even-numbered columns also include region-specific time trends. The effect of the instrument is strongly significant, with an estimate ranging from 0.39 to 0.68. Among the other coefficients, the positive association with the lagged HHI is expected given the use of enrollment-based LIPSA weights from 2009 onward. The large value of the regression \( R^2 \) and \( F \)-statistic for the instrument confirm the strong association of the instrument with \( \text{wLIS}_4 \).

Next, I estimate the reduced-form relationship linking the instrument to the growth in basic premium. In particular, I estimate the following model:

\[
\Delta \ln(b.\text{premium})_{jt} = \alpha + \vartheta(\text{MA-PD}_{2006_j} \times \text{Post}_{2009_t}) + \gamma X_{jt} + \delta Q_{jt-1} + \tau_t + \lambda_j + \epsilon_{jt}.
\]

The box at the bottom of Table 7 reports OLS regressions of \( \Delta \ln(b.\text{premium}) \) on the instrument for the six specifications used for the first stage. The effect of the instrument is strongly significant, with an estimate ranging from 0.21 to 0.47. Among the other coefficients, there is some weak evidence that the lagged HHI increases premium growth and that higher lagged unemployment decreases it. These results confirm the graphical evidence from Figure 6.

B. Results

The results of the IV estimation are reported in Table 8. The box at the top of the table reports OLS estimates for comparison. These estimates indicate that premiums grow faster when the LIS is more prone to manipulations. The estimates range from 0.27, for the model with only region and year dummies as covariates, to 0.35, for the model with all covariates and region time trends. The box at the bottom of Table 8 presents IV estimates obtained via two-stage least squares (2SLS). The effect of the LIPSA weight concentration is estimated to be positive and statistically significant.

\[ \text{Standard errors are clustered by region. This accounts for the level of variation of the instrument.} \]
Panel A. The first stage

Panel B. The reduced form

Notes: Panel A: Total enrollment share of MA-PDs in 2006 and concentration in LIPSA weights, $w_{LIS4}$. Panel B: Total enrollment share of MA-PDs in 2006 and log difference in average basic premium, $\Delta \ln(b\text{-premium})$. Scatter plots of raw data and OLS regression line (no controls). The plots for 2011, not reported, are analogous to those for 2009 and 2010.
### Table 7—First Stage and Reduced-Form Regressions

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A. First stage</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MA-PD$<em>{2006} \times$ Post$</em>{2009}$</td>
<td>0.388***</td>
<td>0.566***</td>
<td>0.460***</td>
<td>0.680***</td>
<td>0.461***</td>
<td>0.668***</td>
</tr>
<tr>
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<td>[0.200]</td>
<td>[0.114]</td>
<td>[0.241]</td>
<td>[0.113]</td>
<td>[0.234]</td>
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<td>HHI</td>
<td>1.566***</td>
<td>1.675***</td>
<td>1.542***</td>
<td>1.959***</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>[0.353]</td>
<td>[0.460]</td>
<td>[0.339]</td>
<td>[0.457]</td>
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<td>Unemployment</td>
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<td>-0.797</td>
<td>-1.050</td>
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<td></td>
</tr>
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<td>[1.320]</td>
<td>[1.800]</td>
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<td></td>
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<tr>
<td>Plan age</td>
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<td></td>
<td></td>
<td>0.034</td>
<td>-0.017</td>
</tr>
<tr>
<td></td>
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<td></td>
<td></td>
<td></td>
<td>[0.059]</td>
<td>[0.071]</td>
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<tr>
<td>Pharmacies</td>
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<td>1.600</td>
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<td></td>
<td></td>
<td>[0.857]</td>
<td>[1.090]</td>
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<tr>
<td>Drugs</td>
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<td></td>
<td></td>
<td>0.133</td>
<td>0.283</td>
</tr>
<tr>
<td></td>
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<td></td>
<td></td>
<td></td>
<td>[0.215]</td>
<td>[0.266]</td>
</tr>
<tr>
<td>Constant</td>
<td>0.249***</td>
<td>-0.366***</td>
<td>-0.019</td>
<td>-0.518***</td>
<td>-0.225</td>
<td>-0.896***</td>
</tr>
<tr>
<td></td>
<td>[0.019]</td>
<td>[0.006]</td>
<td>[0.085]</td>
<td>[0.046]</td>
<td>[0.228]</td>
<td>[0.217]</td>
</tr>
<tr>
<td>Region</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time trends</td>
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<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.951</td>
<td>0.975</td>
<td>0.963</td>
<td>0.980</td>
<td>0.964</td>
<td>0.981</td>
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<tr>
<td>$F_{IV}$</td>
<td>33.91</td>
<td>26.68</td>
<td>46.35</td>
<td>43.38</td>
<td>44.28</td>
<td>40.18</td>
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<td>Observations</td>
<td>170</td>
<td>170</td>
<td>170</td>
<td>170</td>
<td>170</td>
<td>170</td>
</tr>
</tbody>
</table>

| Panel B. Reduced-form |              |              |              |              |              |              |
| MA-PD$_{2006} \times$ Post$_{2009}$ | 0.211***     | 0.349**      | 0.317***     | 0.430**      | 0.345***     | 0.468***     |
|                      | [0.0556]     | [0.167]      | [0.074]      | [0.177]      | [0.068]      | [0.164]      |
| HHI                  | 0.693*       | 0.882        | 0.658        | 0.728        |              |              |
|                      | [0.390]      | [0.585]      | [0.410]      | [0.795]      |              |              |
| Unemployment         | -0.020*      | -0.034       | -0.020*      | -0.030       |              |              |
|                      | [0.011]      | [0.024]      | [0.011]      | [0.023]      |              |              |
| Plan age             | -0.082       | -0.073       |              |              |              |              |
|                      | [0.062]      | [0.106]      |              |              |              |              |
| Pharmacies           |              |              | 0.538        | -0.072       |              |              |
|                      |              |              | [1.230]      | [1.560]      |              |              |
| Drugs                |              |              | -0.313       | -0.322       |              |              |
|                      |              |              | [0.357]      | [0.469]      |              |              |
| Constant             | -0.030**     | -0.103***    | -0.084       | -0.093       | 0.265        | 0.143        |
|                      | [0.0144]     | [0.014]      | [0.062]      | [0.092]      | [0.343]      | [0.465]      |
| Region               |              |              |              |              |              |              |
| Time trends          | No           | Yes          | No           | Yes          | No           | Yes          |
| $R^2$                | 0.464        | 0.634        | 0.498        | 0.653        | 0.511        | 0.659        |
| Observations         | 170          | 170          | 170          | 170          | 170          | 170          |

**Notes:** 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.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

The 2SLS estimates range from 0.54 for the model with only region and year dummies as covariates, to 0.75 for the model with all covariates and region time trends. Relative to their OLS counterparts, all 2SLS coefficients are larger. Although this suggests a downward bias for the OLS, these estimates lie within the 95 percent confidence interval of their 2SLS counterpart. Given the most conservative estimate of 0.27, a one standard deviation increase of wLIS4 would imply an increase in $\Delta \ln(b_{\text{premium}})$ of 6.8 percent. This is a large effect if compared to a sample mean of $\Delta \ln(b_{\text{premium}})$ of just 5.8 percent. In particular, it suggests that the increase in
the average concentration of LIPSA weight, that passed from a value of 0.07 in 2006 to a value of 0.67 in 2011, can explain 49 percent of the increase in the average basic premium, that in this same period passed from $20.50 to $27.34.

This estimate, however, is likely to overstate the effect of LIS manipulations on premiums because the switch to enrollment weighting caused a mechanical increase in the LIPSA from 2008 to 2009. Essentially, as mentioned in Section III, cheap MA-PD plans lost weight that was reassigned to expensive PDP plans. Thus, insurers who correctly foresaw this change might have increased their premiums even absent strategic LIS manipulations. Holding the 2008 premiums fixed, the mechanical
increase in the LIPSA accounts for about one-third of the observed LIPSA increase in 2009, while the rest is due to premium increases. As a rough approximation, it might then be appropriate to take 32 percent (two-thirds of the estimated 49 percent effect) as a more conservative measure of how much of the increased growth in premiums can be explained by strategic manipulations.27

To assess the soundness of the large estimates obtained, it is useful to consider the effects of \( wLIS4 \) on different subsets of plans. The two partitions analyzed are analogous to those used in Table 5. The first partition divides plans into those with LIPSA weight above or below the average. I then calculate the log difference in the average basic premium for each group and use this variable to estimate equation (1). The top panel of Table 9 reports the estimates of \( \beta \) for the same six model specifications of Table 8. The “Yes” row reports the effect on premium growth among high LIPSA weight plans, while the “No” row refers to the complement group. The positive and large effects for the high weight plans are consistent with the expected effect of the \( wLIS4 \). Qualitatively, the results remain the same when replacing the cutoff point with the seventy-fifth or ninetieth percentiles of the LIPSA weight. The bottom part of Table 9 reports similar results for a different partition of plans: those that were LIS-eligible in \( t - 1 \) and those that were not. The plans in the former group are those we might expect to raise premiums in response to a higher LIPSA level and, indeed, this is what the estimates show.

C. Robustness Checks

Below I summarize the results from three sets of robustness checks. The complete set of associated estimates, instead, are reported in the online Appendix. To confirm that it is the 2009 switch to enrollment weighting that drives the results, the first check that I conduct is a placebo analysis for the year of the switch. Hence, I modify the instrument by changing the dummy for the year of the policy change to either 2008 or 2010. When 2008 is taken as the year of the switch, the IV estimates are not significant. When 2010 is used, there is no significant effect of \( wLIS4 \) for the specifications with region time trends, but the effect is significant without including region time trends. Thus, there is no preexisting force that drives the 2SLS estimates, but these estimates might be downward biased, perhaps due to firm learning after 2009.

The second robustness check evaluates two changes in the instrument. First, for a better exploitation of the variability across years, I substitute the single instrument with four instruments obtained by the interaction of the 2006 MA-PD share with year-specific dummies (the excluded year being 2011). The 2SLS estimates are nearly identical to those in Table 8. Moreover, the similarity of the 2SLS and limited information maximum likelihood (LIML) alleviate concerns of weak instruments. Second, to address issues concerning the exogenous nature of the proposed instrument, I perform the analysis with a second set of alternative instruments: the Medicare Advantage shares in 2003, 2004, and 2005. Since Medicare D was not active prior to

27 One additional complication is introduced by the fact that premiums fluctuate not only because insurer bids change but also because the constant that CMS applies to the national average to compute the basic subsidy changes from year to year. To address this issue, I repeated the same analysis using basic bids instead of basic premiums. The results reported in the online Appendix confirm the evidence presented in Table 8, indicating a positive and statistically significant association between bid growth and \( wLIS4 \).
2006, these are shares out of the entire population of Medicare eligibles in the region. However, their geographic variation is rather similar to that in Figure 2 and, indeed, the estimates obtained using any of the MA shares are rather similar. However, there is a gradual tendency for the magnitude of the estimates to decline as we move to instruments based on earlier MA shares and the effect is not significant in the specifications with time trends.

The third set of robustness checks involves the sensitivity of the estimates to the model specification. The first issue that I investigate regards the role of the HHI. The HHI and \( wLIS4 \) are, as expected, positively correlated. Indeed, all the model specifications of the first-stage regression indicate that HHI is significant at the 1 percent level. This suggests that the IV estimates will be biased if the HHI fails to be exogenous. Thus, although in Table 8 the inclusion of HHI does not drastically alter the estimates, focusing on specifications [1] and [2], obtained excluding the HHI, is desirable. Nevertheless, the comparison of all the estimates in Table 8 is interesting because it reveals that, when the HHI is included, its coefficient is not significant while \( \beta \) remains significant. A likely explanation is that the HHI around 2009 does not experience the type of change observed for \( wLIS4 \) and, hence, is unable to account for the increased growth in premiums after 2008. Indeed, the strength of the correlation between HHI and \( wLIS4 \) changes over time: it is 35 percent in the years 2006–2008, while it increases to 55 percent in 2009–2011.

The second issue regarding the model specification that I analyze is the lack of statistical significance of the regression covariates in Table 8. I evaluate the robustness of the estimates in Table 8 to the inclusion of additional controls for insurers’ market power (for both LIS and total enrollment), region demographic characteristics (related to schooling, income, and age), and plan formularies. The results of these alternative specification are in line with the parsimonious specifications in Table 8. This can be explained by both the small size of the sample used

<table>
<thead>
<tr>
<th>Plan LIPSA weight above average</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>0.517***</td>
<td>0.835***</td>
<td>0.692***</td>
<td>1.053***</td>
<td>0.686***</td>
<td>1.075***</td>
</tr>
<tr>
<td></td>
<td>[0.126]</td>
<td>[0.159]</td>
<td>[0.173]</td>
<td>[0.268]</td>
<td>[0.163]</td>
<td>[0.301]</td>
</tr>
<tr>
<td>No</td>
<td>−0.639</td>
<td>−1.250</td>
<td>−1.375**</td>
<td>−1.846**</td>
<td>−1.231**</td>
<td>−1.767*</td>
</tr>
<tr>
<td></td>
<td>[0.551]</td>
<td>[0.785]</td>
<td>[0.514]</td>
<td>[0.824]</td>
<td>[0.481]</td>
<td>[0.960]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Plan LIS eligible in ( t−1 )</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
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<tbody>
<tr>
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<tr>
<td></td>
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<td>[0.241]</td>
<td>[0.464]</td>
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Notes: The table reports estimates of the effect of \( wLIS4 \) on the growth in basic premium for subgroup of plans. The model specifications are the same as those reported in Table 8 with the only difference that the average basic premium in each region is calculated using subgroups of plans: in the top panel, for the “Yes” row the subgroup is that of plans with an above average LIPSA weight. The complement subgroup is used for the “No” row. Enrollment shares: 70 percent in the first partition for the plans above average and 53 percent in the second partition for LIS-eligible plans in \( t−1 \).

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.
and the low degree of differentiation in the characteristics of basic PDPs. Indeed, Duggan and Scott Morton (2011) show that it is hard to explain premium growth using conventional measures related to drug costs. Finally, additional results using alternative measures of both LIS manipulability and premium growth are presented in the online Appendix. Overall, these findings broadly confirm that the increased LIS manipulability is a quantitatively important cause of the premium growth.

VI. Conclusion

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 increase in premiums. 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 reveals two important facts. First, for five of the seven largest insurers there are multiple indications that premium distortions occurred. However, these firms are heterogeneous with respect to the strategy they adopt to take advantage of the loopholes in the LIS regulations. Second, increases in the concentration of LIS weights at region level have been shown to be positively associated with premium growth, likely accounting for a large share of the premium growth in the sample period.

These findings are important because they complement those of Duggan and Scott Morton (2011) and Ericson (2014) regarding the sources of premium growth. Moreover, they also complement the vast literature on the consumer choice of plans in Part 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, premiums unlikely reflect the true underlying cost conditions and, hence, cannot guarantee efficiency.

These findings indicate the need to reform the LIS regulations to prevent premium manipulations. Among the solutions that could solve the problem described in this paper, the more drastic would be to offer drugs to LIS enrollees through a public plan. This could be achieved, for instance, by returning to a system similar to the Medicaid drug coverage system, as advocated by the studies referenced earlier. An advantage of this solution would also be to guarantee that all LIS enrollees are treated equally, something that the current random assignment system is not capable of achieving. The same effect could be achieved through another drastic reform that would consist of allocating all LIS enrollees in a region to the same private plan willing to offer the lowest price to the government to serve them. After having set rigid standards on the admissible formularies and pharmacy networks, this could be implemented through a sealed bid auction, or even through a combinatorial auction to exploit the possible economies of scale achievable by operating in multiple markets.

Although both solutions described above have the potential to eliminate LIS manipulations, they are likely to have profoundly different effects on insurers’ behavior. Indeed, albeit both have drawbacks, it is worth to note that separating LIS enrollees from the rest of the market removes not only the incentives to manipulate the premiums upward, but also the downward pressure on the premiums of non-manipulating insurers. Instead, assigning all LIS enrollees to the cheapest plan, or even preserving
the current system but forbidding within-firm reassignments, could preserve the downward pressure. Although the findings in this study are indicative that such downward pressure was unable to counterbalance LIS manipulations during the period analyzed, its potential effectiveness to limit premiums growth is likely relevant.\footnote{Quantifying the effects of the downward pressure under these counterfactual market arrangements would likely require estimating a structural model. A baseline calculation of a bound on this effect is presented in the online Appendix combining the simple model presented there with the findings in Table 5. A more sophisticated analysis, however, would require cost data since the strength of the downward pressure crucially depends on the cost of insuring LIS enrollees and on the presence of adverse selection. Polyakova (2014) uses such data form enrollees’ drug purchases to show the presence of adverse selection among the regular Part D enrollees.}

Less radical solutions would also be possible but their effectiveness would depend on the finer details of their implementation. For instance, the “intelligent assignment” employed in Maine entails an element of negotiation between the State and the insurers that allows the latter to decide whether or not they want to receive LIS enrollees. Within an adequate system, giving this option to insurers can be useful to limit pricing distortions. As regards specifically the LIPSA calculation, amending the current system in such a way that the LIPSA is calculated not on the basis of current bids, but on the basis of historical bids, or even costs, would reduce manipulations. Similarly, premium distortions could likely be reduced if the LIPSA were: a fixed amount chosen by CMS every year, or a fixed percentage of each premium, or a fixed percentage of the national average, or proportional to a fixed percentage of the enrollee’s income. The argument made about the difficulty of manipulating the national average also suggests that a third simple solution would be to dilute the weights that each plan exercises on the LIPSA. This could be achieved, for instance, by using national instead of regional weights. In this respect, the plan consolidations forced by the 2011 reform is a source of concern since it caused greater enrollment concentration into fewer plans without eliminating the possibility of manipulations. This concentration makes the correct design of the statistics used to regulate the market particularly important. Moreover, it suggests the urgent need to close the loophole of the 2001 meaningful difference reform by forcing even multibrand insurers to have a single basic PDP and forbidding switches between basic and enhanced status.

Finally, the risk of firms’ collusion in the presence of particularly few plans determining the LIPSA deserves to be mentioned. When firms’ profits are linked to average-based statistics, like the LIPSA, the risk of collusion is stronger than in traditional markets because even firms that are not competitive might be relevant to engage in strategies aimed at manipulating the average. Indeed, a few large-scale collusion cases, most notably the manipulation of the LIBOR, have been documented under this type of average-based mechanism.\footnote{One episode is the London Interbank Offered Rate (LIBOR) scandal which exploded in the summer 2011, while a second one involves the Average Bid Auctions used in public procurement and is documented in Conley and Decarolis (2013).} The LIS design should be reformed without waiting for similar episodes to occur.
REFERENCES


