Healthcare Plans and Patient Outcomes: Evidence from Bankruptcy-Induced Random Assignment in Colombia*

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ABSTRACT: We examine the effect of random assignment to health insurance plans on mortality and healthcare utilization. Our data are from Colombia, which provides a unique context to study how health plans affect outcomes. First, the entire public healthcare system is a form of "managed competition" where profit-seeking firms receive government subsidies to provide healthcare to patients, with the exact same financial coverage. Second, when health insurance firms go bankrupt, which happens with some frequency, patients are randomly assigned to remaining firms by a government scheme that mimics a "shift-share" instrumental variable. We exploit this random assignment to assess how different insurances companies affect patients. We first provide evidence that random assignment works as intended: actual assignment is nearly identical to what the government's randomization scheme would suggest. Two, we show that bankruptcies in general lead to lower average mortality, suggesting that firms going bankrupt do a relatively poor job of keeping patients alive and that "managed competition" helps remove particularly bad firms from the market. Third, we show healthcare utilization declines following a bankruptcy, which we attribute to the reallocation of patients to more efficient health insurers.

KEYWORDS: competition, health insurance, morality, healthcare utilization
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1 Introduction

National health insurance schemes increasingly include privately administered health insurance plans. For example, in the U.S., roughly one half of seniors opt for Medicare Advantage, which means various private firms can compete to insure them, rather than getting covered by the public insurance option Traditional Medicare. Usually, firms in such markets are highly regulated and thus comparable along key dimensions, including cost-sharing, out-of-pocket costs and services covered. This type of arrangement is sometimes called “managed competition” in healthcare markets. Similar approaches are used in other contexts where the government reimburses private firms to deliver public benefits (e.g., schools, public housing, and childcare). A natural question is whether, under such strict and uniform regulation, there is room for discernible quality differences. In other words, do private health insurance plans affect patient outcomes in highly regulated markets and if so, why?

This paper examines the impact of health insurance plans on patient outcomes in Colombia. The Colombian public healthcare scheme is compulsory and covers all citizens. Key features resemble Medicare Advantage—in each market (defined by municipalities, of which there are 1,104), multiple firms offer health insurance, with the exact same premium and cost sharing, and patients may choose among them. To investigate insurers’ quality effects, we leverage a unique feature of the Colombian policy environment that induces random assignment to insurance providers. Firms frequently exit the market through bankruptcy and their patients are randomly assigned to surviving firms—firms in the same municipality that did not go bankrupt. Randomly assigned individuals are not allowed to change their insurance plan for three months—thus creating quasi-random variation in patient-firm matches. Our aim is to assess whether assignment to plans leads to measurable differences in patient outcomes (e.g., healthcare utilization and mortality).[1]

In Colombia, there are several bankruptcies in many different municipalities, leading to rich quasi-experimental variation. Between 2019 and 2022, 10 bankruptcies occurred, leading to the transfer of over 1,285,227 patients to 11 surviving firms in 589 municipalities. In total, there are 1,121 municipality-bankruptcy events, each of which leads to a plausibly exogenous reassignment of patients to firms. Our analysis leverages this source variation to measure plan effects on patient morality and healthcare utilization outcomes.

We provide three key sets of findings. First, we show that the rule-based algorithm functions as intended in that the predicted probabilities of which patients the algorithm predicts would shift to another firm within a market line up with what is observed in the data. This analysis validates the experimental variation we exploit to measure plan effects

[1] Throughout this paper we refer to firms and plans interchangeably.

on patient outcomes.

Second, to provide *prima facie* evidence that firm quality matters, we consider the impact of bankruptcies in general on municipality level mortality. The idea is to assess whether the reassignment of patients to surviving firms leads to a net increase or decrease in mortality. One could imagine that exiting firms went bankrupt because they were too generous in managing an individual's healthcare consumption. Transfers to a surviving plan in the market could lead to worse patient outcomes once they are moved to (potentially) less generous firms. However, we find that exits and resulting reassignment leads to a net reduction in mortality. On average, for a 1 percentage point increase in the market share of the bankrupt insurance plan, the municipality mortality rate falls by 0.111 percentage point. To put this into perspective, in a municipality with 100,000 people, if 1,000 are reassigned due to bankruptcy, the municipality will exhibit 1 fewer death in the three months following the move.

Our third finding quantifies the impact of bankruptcies on healthcare utilization. We estimate that following a bankruptcy episode, the rate of healthcare utilization within a municipality decreases. Specifically, for a 1 percentage point increase in the market share of a bankrupt EPS, healthcare utilization following the random assignment of its affiliates declines by 3,650 pesos per-affiliate. This reduction in healthcare utilization is consistent with individuals moving to more efficient firms that are able to better manage healthcare utilization costs, unlike the those that went bankrupt.

Our paper relates to prior studies of the health effects of insurance plans. The closest to ours is Geruso et al. (2023). The authors exploit random assignment of individuals to Medicaid managed care plans in New York City. This source of variation allows the authors to identify plan-specific effects on outcomes like healthcare spending and health outcomes. They document significant heterogeneity in plan-specific effects on these outcomes despite having identical cost sharing designs. These effects manifest in plans broadly reducing the consumption of needed and unneeded care, which can reduce beneficiary health. Wallace (2023) documents how some of the variation in plan-effects can explained by different provider networks across plans but significant differences remain. We complement these findings by recovering distributions of plan-effects by using large scale experimental variation across markets and heterogeneous individuals as well as outcomes like healthcare utilization and mortality. Other work has quantified the effects of health insurance using other identification strategies. For example, Abaluck et al. (2021) develop a novel IV strategy based on plan cancellations to estimate mortality effects of Medicare Advantage plans. Goldin et al. (2020) also estimate the affect of health insurance on mortality using a large scale experiment of randomly "nudging" uninsured individuals to purchase coverage. Similar to our analysis, these studies find insurance coverage does have causal effects on mortality.

We also connect to studies using Bartik instruments. Goldsmith-Pinkham et al. (2020) provide a framework for understanding when Bartik research designs are identified. Our setting is close to the canonical examples they consider. As we will demonstrate, bankruptcies within a municipality are a common shock to all firms, while the size of an individual firm's shock depends on their pre-bankruptcy market shares. This exposure research design allows us to look at how differential exposure to the common shock (i.e., a bankruptcy) allows us to identify differential *changes* in the outcomes of interest. A methodological contribution of our study is to demonstrate how to derive and implement a Bartik research design from an individual-level model that can be estimated in aggregate data, which may be more readily available to researchers than individual-level data resources.

Finally, we contribute to a growing literature focusing on the healthcare system in Colombia. Examples include Posso et al. (2022), who examine the affects of physician quality—as measured by exam performance—on birth outcomes using the random assignment of Colombian doctors to patients; Serna (2023), who studies how health insurers engage in risk selection through the formation of hospital networks; and Buitrago et al. (2023a), which quantifies the causal links between insurance cost sharing designs and mortality. Closely related to our analysis is Buitrago et al. (2023b), who studies the mortality effects of hospital networks—a key margin of plan differentiation under this regulatory setting. The authors document an increase in mortality as individuals are assigned to narrower networks plans and face capacity constraints in readily accessing care. This channel is particularly relevant for the sickest patients. Our contribution highlights the various quality differences that can arise under a highly regulated system like Colombia's and how these differences vary across different types of markets. These lessons are broadly important for the design of healthcare policies in other countries which use private health insurance firms to deliver public healthcare benefits.

The paper proceeds as follows. In Section 2 we describe the setting and assignment algorithm. We discuss our data sample and sources in Section 3. In Section 4 derives the econometric models we estimate. Our estimates are presented and discussed in Section 5. Section 6 concludes.

2 Background and Random Assignment

The healthcare system in Colombia resembles a private market but features a significant level of government regulation of health insurance companies and healthcare providers. By law, every citizen in the country is entitled to health insurance coverage and participation in the public health insurance system is compulsory for all citizens. Similar to the Medicare

Advantage program in the United States, plans offered by the public system are administered and marketed by private and public insurers (typically referred to as EPS). Beneficiaries must choose among the EPS plans available to them in their local market (i.e., municipality). There is a complementary small private insurance market that competes with EPS plans but covers only 2.4% of beneficiaries nationally (DANE, 2020).

As part of the country's managed competition scheme, the Colombian Ministry of Health heavily regulates the cost structures of plans provided by EPS. They explicitly set out what premiums, copayments, coinsurance, and out-of-pocket maximum amounts are permitted. The ministry allows for modest rate differentiation based on a beneficiary's monthly income.[2] However, conditional on a beneficiary's characteristics, each EPS is only differentiated by the size, composition, and quality of the provider network it has established and how well the EPS processes medical claims. Provider networks are formed by contracting with specific healthcare providers (IPS) where enrollees in a plans may receive care.[3] Thus, EPS firms have incentives to contract with high-quality IPS and to implement systems that process medical claims promptly to attract enrollees. These incentives are weighed against concerns about selection and the extra cost they pay impose on an EPS. Prior work has documented how Colombian insurance firms strategically design their provider networks as a risk selection mechanism (Serna, 2023).

The Colombian government has adopted a novel systematic policy to meet their legal requirement to maintain a citizen's access to healthcare when an EPS enters bankruptcy. Specifically, beneficiaries in a bankrupt EPS are automatically reassigned to a financially solvent EPS in their market according to a well defined formula. Impacted beneficiaries are split into two groups. The first group is composed of beneficiaries in the "high cost account" that have conditions which are costly to cover (e.g., diabetes, HIV, cancer, etc.). These people are randomly assigned to a new EPS. The second group is composed of all other beneficiaries from the bankrupt EPS. Half of these people are randomly assigned to a new EPS in their local market, while the other half are assigned to a new EPS proportional to market shares. Impacted beneficiaries cannot choose their new EPS and are obligated to remain in their EPS for at least three months.

[2]EPS firms receive a fixed monthly capitation payment from the government for each beneficiary enrolled in the plans they offer. These payments are risk adjusted for beneficiaries that have conditions that are costlier to cover.

[3]The use of "IPS" broadly refers to any hospital, clinic, or laboratory where a beneficiary receives care.

3 Data

From 2019 we observe enrollment in an EPS at the EPS-municipality-month level. These data cover 53% of municipalities in Colombia (roughly 60% of the population and all of its major cities) from 2019–2022. These panel data allow us to see how enrollment changes over time—in particular—following bankruptcy episodes. Moreover, we observe shifts in enrollment at observable levels that are relevant for the assignment algorithm used by the Colombian government. Thus we have a panel of EPS-municipality-bankruptcies.

Our outcome measures come from Vital Statistics Records and aggregate individual medical claims data called RIPS. From Vital Statistics, we observe total mortality at the EPS-municipality-month level. RIPS allows us to observe medical claims for the entire population from January 2008 to February 2022. Our analysis focuses on claims from 2019–2022. A limitation of RIPS is that they do not contain payment information. To convert these claims into a measure of healthcare utilization we apply information from the SOAT legal manual, which contains reference prices for all medical procedures and consultations. We apply reference prices from December 2019.[4] Since the RIPS data are at the individual level, we aggregate them to the EPS-municipality level for our current analysis.

The unit of analysis for the aggregate models we estimate is a EPS-municipality-bankruptcy. Our main independent variable of interest is the change in market shares one month before vs one month after a bankruptcy event for each EPS-municipality dyad. To calculate changes, we first define market shares as the number of individuals affiliated with an EPS in the municipality divided by the total number of individuals in the municipality. We calculate market shares for one month before and one month after the bankruptcy and then take the difference. In cases where an EPS that went bankrupt was not operating in a municipality, the changes in market shares are approximately zero and only due to small fluctuations (e.g., due to deaths or people switching their EPS, which happens very infrequently). In total, we have 1,120 municipality-bankruptcy pairs. While our independent variable of interest is the actual change in market shares, we are also interested in the *expected shifts in market share* as predicted by the government assignment rule. To calculate this quantity, we use the same pre-bankruptcy market shares and then use the assignment rule to calculate the predicted post-bankruptcy market shares, divided by total affiliates and then take the difference.

Our main dependent variables of interest are the change in the municipality mortality rate and the healthcare utilization rate for EPS affiliates in a municipality.[5] As we outline

[4] A small number of procedures and consultations do not appear in the SOAT manual. In these cases we apply prices paid by the largest EPS in the country. See Appendix B for a detailed discussion of how the utilization metric is constructed.

[5] The mortality rate is defined per 100,000 affiliates and the utilization rate is defined in thousands of

below when developing our framework, the focus is on changes in these variables among individuals who covered by an EPS that survives the bankruptcy and receives patients since this is the relevant population (i.e., the population who is directly affected by a bankruptcy).

Nearly half of all municipalities in Colombia experienced at least one bankruptcy episode during the period 2019–2022. Figure 1 plots the distribution of the number of bankruptcies by municipalities that experienced at least one bankruptcy. It is common for municipalities to experience multiple bankruptcies. Over 50% of municipalities exposed to an EPS bankruptcy experienced at least two of these events. Table 1 shows the descriptive statistics of the aggregate variables. Following a bankruptcy there are typically three EPS active in a municipality, with slightly more firms present in larger markets. On average, a firm that does not go bankrupt sees an increase in their market share of about 12%. The typical change in market shares is larger in markets with smaller populations. Notably the observed changes in market shares closely align with the changes predicted by the assignment algorithm used by the Colombian government.

The bottom two panels of Table 1 report information on our outcomes of interest. Following a bankruptcy, the mortality rate falls. This decline is slightly greater for municipalities with smaller populations but there is substantially more variation in the mortality rate among these markets than in their larger counterparts. Following a bankruptcy there is an increase in the average healthcare utilization rate. This growth in healthcare utilization is primarily driven by markets with larger populations. Quantifying whether these changes have a causal attribution to the surviving EPS plans is the aim of our empirical analysis.

4 Econometric Models

In this section we illustrate how to derive the aggregate models we estimate from the individual level where the random assignment to plans occurs following the bankruptcy of an EPS.

4.1 Individual level

Consider the following individual level outcome model:

$$Y_{im,t} = T_{im1,t}\phi_1 + \cdots + T_{imJ,t}\phi_J + e_{im,t} \tag{1}$$

pesos per-affiliate.

where $Y_{im,t}$ is outcome Y for individual i in municipality m. $T_{imj,t}$ is a dummy variable indicating individual i in m is affiliated to EPS j at time t and that j is in the set of available EPS's in the municipality $\mathcal{J}_m$. To simplify notation, we allow there to be J total EPS's in the model.[6] The ϕ_j's map EPS's to the outcome and are the coefficients of interest. $e_{im,t}$ is a disturbance term.

A well known challenge for identifying the ϕ_j parameters is that treatment (here, assignment to an EPS) could be endogenous. It might be the case that healthier individuals sort into better plans in which case we are not capturing EPS quality but instead unobserved individual level characteristics that affect health outcomes. This is a classic "selection into treatment" or more generally "omitted variables bias" problem.

The bankruptcy assignment algorithm allows us to overcome this challenge. Given the formula for the assignment algorithm we can quantify the probability that an individual enrolled in the bankrupt EPS will be assigned to a new EPS in their municipality. In essence this is an experiment that occurs at the individual level. Given the assignment algorithm we can express the probability that individual i is assigned to EPS j following the bankruptcy of EPS k as:

$$Z_{ijm,t} = L_{im,t}\frac{1}{2}\left(\frac{1}{|\mathcal{J}_{m,t-1}|-1} + \frac{MS_{mj,t-1}}{1-MS_{mk,t-1}}\right) + (1-L_{im,t})\frac{MS_{mj,t-1}}{1-MS_{mk,t-1}} \tag{2}$$

where L is an indicator for whether individual i is a member of the low cost account and MS denotes the market share of an EPS within municipality j.

This assignment rule is a source of exogenous variation in plan assignment and can be used as an instrument in a first stage equation. Formally:

$$T_{imj,t} = Z_{im1,t}\psi_1 + \cdots + Z_{imJ,t}\psi_J + \epsilon_{ij,t} \tag{3}$$

where assuming compliance, the coefficients ψ_{jm} should be close to 1. Moreover, these probabilities ought to sum to 1 (i.e., $\sum_{j\in\mathcal{J}_m} Z_{imj,t} = 1$).

For $Z_{ijm,t}$ to be valid instrument it must predict enrollment, be uncorrelated with the unobservables $\epsilon_{imj,t}$ and $e_{imj,t}$, and only impact the outcome of interest $Y_{im,t}$ through assignment to a plan $T_{im,t}$. The bankruptcy assignment algorithm used in Colombia clearly satisfies these conditions for the individuals enrolled in a bankrupt EPS. The algorithm has a closed form expression for the probability that an individual is assigned to each of the remaining plans post-bankruptcy, so it is predictive of enrollment. The assignment feature includes a lock-in period where moved individuals are unable to switch out of their new EPS

[6] This is a slight abuse of notation as J could be different by t and m and should be indexed as $J_{m,t}$.

for three months, which attenuates concerns about non-compliance and a possible correlation with the first stage unobservable $\epsilon_{im,t}$. The instrument is a constant within-municipality probability which is likely to be uncorrelated with the unobservable factors captured by $e_{im,t}$ that impact the outcome $Y_{im,t}$. As a result, the only way for the instrument to impact the outcome is through assignment to a new EPS $T_{ij,t}$.

4.2 Aggregate level

Now we demonstrate how to derive the aggregate model from the individual level model. We start by summing over all individuals in the municipality:

$$\sum_{i\in m} Y_{im,t} = \sum_{i\in m} T_{im1,t}\phi_1 + \cdots + \sum_{i\in m} T_{imJ}\phi_J + \sum_{i\in m} e_{im,t} \tag{4}$$

$$Y^{TOT}_{m,t} = N_{m1,t}\phi_1 + \cdots + N_{mJ,t}\phi_J + e^{TOT}_{m,t} \tag{5}$$

Note that each municipality has different population sizes. Thus, the sum should be for i in m where m is indexed with t, but we are keeping notation simple. Here $Y^{TOT}_{m,t}$ is the total outcome in municipality m at time t (e.g., total deaths, total utilization, etc.). It is a function of the total number of people in each EPS, which is denoted $N_{mj,t}$. This value is simply what we obtain by summing dummy variables to collapse the individual level data to the municipality level. $e^{TOT}_{m,t}$ is a municipality-level disturbance.

Take the above model and divide by the municipality's population, which we can denote $N_{m,t}$. We can obtain similar expressions for period t after a bankruptcy and period $t-1$ before a bankruptcy. Differencing them yields:

$$Y^{RATE}_{m,t-1} = MS_{m1,t-1}\phi_1 + \cdots + MS_{mJ,t-1}\phi_J + e^{RATE}_{m,t-1} \tag{6}$$

$$Y^{RATE}_{m,t} = MS_{m1,t}\phi_1 + \cdots + MS_{mJ,t}\phi_J + e^{RATE}_{m,t} \tag{7}$$

$$\Delta Y^{RATE}_{m,t} = \Delta MS_{m1,t}\phi_1 + \cdots + \Delta MS_{mJ,t}\phi_J + \Delta e^{RATE}_{m,t} \tag{8}$$

where the LHS variable is a within-municipality shift in the outcome and the RHS variables are pre-bankruptcy to post-bankruptcy shifts in market shares of surviving EPS plans. This formulation allows us to relate shifts in market shares to the outcomes of interest.

To build intuition for what effects we can identify at the aggregate level it is helpful to consider a specific example. Suppose $J_{mt} = 3$ in period $t-1$ and between period $t-1$ and period t EPS3 goes bankrupt. Then we have the following:

$$Y_{m,t-1}^{RATE} = MS_{m1,t-1}\phi_1 + MS_{m2,t-1}\phi_2 + MS_{m3,t-1}\phi_3 + e_{m,t-1}^{RATE} \tag{9}$$
$$Y_{m,t}^{RATE} = MS_{m1,t}\phi_1 + MS_{m2,t}\phi_2 + e_{m,t}^{RATE} \tag{10}$$

Subtracting these equations gets us the change in the outcome rate from $t-1$ to t:

$$\Delta Y_{m,t}^{RATE} = \Delta MS_{m1,t}\phi_1 + \Delta MS_{m2,t}\phi_2 - MS_{m3,t}\phi_3 + \Delta e_{m,t}^{RATE} \tag{11}$$

Given the government reallocation policy, the change in market shares for EPS1 and EPS2 should approximate the market share of the bankrupt EPS: $MS_{m3,t} = \Delta MS_{m1} + \Delta MS_{m2}$. After substituting into the previous equation this yields the following estimation equation:

$$\Delta Y_{m,t}^{RATE} = \Delta MS_{m1,t}\mu_{1,3} + \Delta MS_{m2,t}\mu_{2,3} + \Delta e_{m,t} \tag{12}$$

where $\mu_{1,3} = \phi_1 - \phi_3$ and $\mu_{2,3} = \phi_2 - \phi_3$. The implication is that the aggregate model can only identify plan effects *relative* to the bankrupt EPS.

The prior derivation breaks out each EPS effect separately. Using a similar approach we can derive another expression that aggregates surviving EPS firms together. This specification allows us to estimate the municipality level effect of a bankruptcy. Formally:

$$\Delta Y_{m,t}^{RATE} = \varphi \sum_{j\in\mathcal{J}_{m,t}} \Delta MS_{mj,t} + \Delta e_{m,t} \tag{13}$$

where φ captures the effect of the surviving EPS on the outcome relative to the bankrupt firm.

Now we turn to the instrument based on the assignment algorithm. We perform a similar aggregation: we sum across individuals within a municipality, divide by the size of the municipality, and the difference periods pre- and post-bankruptcy. This procedure yields the following expression:

$$\Delta Z_{mj,t} = \frac{MS_{k,t-1}^{L}}{2}\left(\frac{1}{|\mathcal{J}_{m,t-1}|-1} + \frac{MS_{mj,t-1}}{1-MS_{mk,t-1}}\right) + MS_{k,t-1}^{H}\frac{MS_{mj,t-1}}{1-MS_{mk,t-1}} \tag{14}$$

where MS^L and MS^H denote the market share of individuals in the low and high-cost accounts within the bankrupt EPS.

Notice that a surviving firm's change in market share is largely determined by their relative market shares within a municipality in period $t-1$. This is essentially a shift-share or Bartik instrument. From here we can define the first-stage equation as:

$$\Delta MS_{mj,t} = \alpha + \sum_{\ell \in \mathcal{J}_{m,t}} \beta_\ell \Delta Z_{mj,t} + X_m' \Gamma + \epsilon_{mj,t} \tag{15}$$

where the coefficients of interest are the β's and should be close to 1.

Next we discuss endogeneity and identification under this shift-share instrument. The main concern with shift-share instruments is that the "shift" or "share" component are endogenous. Identification is strongest if pre-bankruptcy market shares for each EPS and the size of the bankruptcy shock are uncorrelated with other factors that can shift the outcome within a municipality (i.e., $MS_{mj,t-1} \perp \epsilon_{mj,t} \; \forall \; j \in \mathcal{J}_{m,t-1}$). To the extent this condition does not hold, we can consider alternative formulations of the instrument. Suppose we are concerned the "shift" is endogenous. Some possible interpretations include large bankruptcies tend to occur in certain types of municipalities, EPS firms chose to enter certain municipalities because of factors that affect changes in outcomes that are not captured by the econometrican, among others. One method employed in the shift-share literature is to "de-localize" the instrument to attenuate these concerns. For example, rather than using the relative size of the EPS that went bankrupt as the "shift" in the instrument, we could use the average size of the EPS in all of the municipalities where it was present. Another strategy from the literature is to use pre-shock (i.e., bankruptcy) shares to address "share" endogeneity. An attractive feature of our setting is that the Colombian assignment algorithm does this automatically. In the empirical analysis our main results use versions of the instrument based on the algorithm described in Equation (14). Future iterations of our analysis will add robustness tests that consider versions of the instruments that employ these de-localization methods.

4.3 Estimation Equations

Here, we briefly repeat the equations we estimate. In Section 5.1, we will validate the assignment rule functions as intended at the aggregate level and in Section 5.2 we use the aggregate model to quantify the effects of bankruptcies on municipality mortality and utilization outcomes.

First stage. We estimate the following first stage equations at the aggregate level:

$$\Delta MS_{mb} = \alpha + \beta \sum_{\ell \in J_{mb}} \Delta Z_{m\ell b} + X_m' \Gamma + \epsilon_{mb} \tag{16}$$

As discussed previously, the first stage outcome for the aggregate models are the change in market shares in municipality m as the result of bankruptcy b. The instrument, denoted by Z, captures the changes in market shares stemming from the assignment algorithm. Our primary specification looks at the total change in market shares for remaining plans after the bankruptcy. We present results in Appendix A, which capture changes in the market shares for each remaining plan. Notice that these instruments vary at the municipality-bankruptcy level, consistent with the randomization produced by the algorithm. We allow for municipality controls and fixed effects to enter these models through $X_m'\Gamma$.

Second stage. We then estimate the following second stage equations at the aggregate level:

$$\Delta Y_{mb} = \alpha + \beta \Delta \hat{M} S_{mb} + X_m'\Gamma + e_{mb} \tag{17}$$

These estimates are obtained by regressing the fitted values for the post-bankruptcy change in market shares from the first-stage onto the change in the outcome of interest ΔY. Results that breakout each EPS plan separately are presented in Appendix A.

5 Results

5.1 Assignment Rule

First we examine whether the assignment rule works as intended. Figure 2 compares the distributions of the observed shift in market shares to the shifts in market shares predicted by the assignment algorithm. The two distributions look quite similar, which suggests that the assignment procedure is operating correctly. We test this formally by estimating the first stage equation (16) that we derived in the previous section. Recall that the first stage outcome is the change in market shares following a bankruptcy and the instrument is the change in market shares predicted by the assignment algorithm. If the assignment algorithm is valid, then we should obtain coefficient estimates on the instrument close to 1.

Table 2 reports estimates of equation (16), which aggregates all surviving EPS firms together. The first column reports estimates for all municipalities in our sample. We find that the coefficient estimate on the algorithm predicted change in market shares is 0.922 and statistically significant. Since the coefficient estimate is close to 1, we take this as statistical evidence that the assignment algorithm functions as a valid first stage equation.

The remaining columns in the table estimate the same model on subsets of municipalities. These groupings are based on quartiles for the total number of affiliates within a municipality. It is notable that most of the municipalities in the sample have a small number of affiliates.

For example, the cutoffs for the first three municipality size quartiles are 10,224, 21,470, and 45,189 affiliates respectively. In other words, roughly 62% of municipality-bankruptcy observations occurred in a municipality with fewer than 50,000 affiliates. While the first stage estimates are consistent for these sub-samples there are two noteworthy observations. First, the coefficient estimate on the instrument gets closer to one for municipalities with more beneficiaries—in the smallest municipalities the coefficient estimate is 0.899 while in the largest it is 0.978. Second, the size of the average change in market shares following a bankruptcy is larger for smaller municipalities. These larger changes in market shares are mechanically driven by the smaller denominator in these geographies. In light of these patterns, we will also present our second stage estimates overall and broken out by these municipality groupings.

Appendix Table A1 reports the estimates for a first stage model that breaks out each EPS. These specifications estimate the change in market share for a specific EPS, while controlling for the changes in market shares for all other EPS firms in a municipality. In general the takeaways from these estimates are similar to what we found in the specifications that aggregated all surviving EPS firms together. We tend to see coefficient estimates around 1, which indicates the assignment algorithm is operating as correctly at the EPS level. The estimated coefficients typically get larger when estimated on a sample with more populous municipalities but there is some heterogeneity in this pattern across firms.

To summarize, our estimates test the validity of the Colombian bankruptcy assignment algorithm as a first stage instrument. We document that the formula appears to work as intended and is highly predictive of the changes in EPS market shares within a municipality following a bankruptcy event. The first stage is strongest in larger municipalities than smaller ones and holds when looking at all EPS pooled together and separately. While these findings are not terribly surprising, they have yet to be documented formally. Moreover, these estimates establish the validity of the experimental variation we use to estimate plan effects and demonstrates how future studies can make use of this variation.

5.2 Mortality and Healthcare Utilization

Having established the validity of the first stage at the aggregate level, we turn our attention to quantifying whether these bankruptcies affect patient outcomes. It is possible that there is no effect, which would suggest that plans do not matter. It is also plausible that the plans have some positive impacts, which may not be surprising since prior work has demonstrated plans can have significant impacts on outcomes like healthcare utilization. The extent to which plans do affect outcomes raises larger questions about how governments ought to regulate or manage competition in these markets. In this section we report estimates for equation (17), which is the second stage model we derived in the prior section for the average municipality level effect of the bankruptcy. This model is estimated using two stage least squares with the assignment algorithm as the instrument.

Table 3 contains our estimates of equation (17) for mortality outcomes within a municipality. When looking at all bankruptcy-municipality observations, we estimate that following a bankruptcy for a 1 percentage point increase in the change in market shares the municipality death rate falls by 0.111 per 100,000 affiliates. This estimate is only marginally significant however. When we re-estimate this model on the groupings of municipalities by affiliate population an interesting pattern emerges. In the first three quartiles we estimate there is no statistically significant relationship between the bankruptcy induced change in market shares and mortality in a municipality. In the fourth quartile we estimate a larger and highly significant mortality effect. In these municipalities we find that a 1 percentage point change in market shares due to a bankruptcy event leads to a 0.302 decline in the mortality rate per 100,000 affiliates. This variation across municipalities contextualizes the pooled estimate and is apparent in the raw data. As shown in Figure 3, smaller municipalities experience substantial shifts in market shares following a bankruptcy but only modest changes in the mortality rate. These large changes in market shares are likely mechanical since, all else equal, any size bankruptcy will result in larger changes in market shares when the size of the affiliate population is relatively smaller. This feature introduces some noise to our pooled estimates that filters out when looking at groups of municipalities by size. Taken together, we view these findings as evidence that plans do have significant impacts in lowering mortality in the short run, especially in geographies with larger populations.

Next we assess what impact these bankruptcies had on healthcare utilization within municipalities. We estimate another version of equation (17) that uses a measure of healthcare utilization constructed from the RIPS data as the outcome variable. These estimates are presented in Table 4. Following a bankruptcy we find that for a 1 percentage point change in market shares, healthcare utilization within a municipality falls by 3.742 thousand pesos per-affiliate. Similar to the mortality rate we document substantial heterogeneity in this effect across municipality sizes. The municipalities in the first quartile see an increase in healthcare utilization (roughly 9.5 thousand pesos per-affiliate), while we estimate reductions of nearly 7 and 18 thousand pesos per-affiliate for the third and fourth quartiles respectively. We find there is no statistically significant effect on utilization in the second quartile. As shown in Figure 4, municipalities with smaller populations have substantial variation in market share changes following a bankruptcy which may introduce noise into some of these estimates. On balance, the effects we estimate are consistent with individuals getting reassigned from less efficient firms to more efficient ones. Bankrupt firms likely lacked the expertise in managing healthcare consumption, which may have contributed to their insolvency.

We can also look at variation in these effects by EPS. These results are presented in the Appendix A. The reason we do not present these as part of our primary estimates is that the instrument specification we rely on purely follows the assignment algorithm and doesn't attempt to resolve potential endogeneity concerns in the market share shifts certain firms face. Future extensions of our analysis will address these endogeneity problems by de-localizing the shifts within the Bartik instrument.[7]

6 Conclusion

This paper examines the affects of health insurance companies on patient outcomes. Our setting is Colombia, which has a managed competition healthcare system that features private firms competing to provide government sponsored healthcare insurance. These private firms frequently go bankrupt and when these events occur, individuals are randomly assigned to a new insurance provider. We leverage this exogenous variation to overcome classic endogeneity problems associated with health plan choices and sorting.

We report three broad empirical findings. First, we document the empirical performance of the assignment algorithm as a first stage. We find that the assignment algorithm is a strong first stage and performs best in municipalities with medium to large populations. The second result uses this variation at the aggregate level data to estimate the impact of bankruptcies on mortality outcomes. Following the bankruptcy of an EPS firm, we estimate significant reductions in the mortality rate within a municipality. These effects do not manifest in small municipalities where relatively small numbers of affiliates introduce substantial noise in the measure of market shares following a bankruptcy. Our third finding evaluates the impact of these bankruptcies on healthcare utilization within a municipality. We estimate that there are significant reductions in healthcare utilization on average after affiliates are assigned to new a EPS following a bankruptcy event. These impacts are driven by markets with larger populations where there is less variation in the change in market shares due to the bankruptcy. We interpret these utilization declines as the result of affiliates moving to health plans that are more adept at managing the healthcare consumption of their enrollees.

Our preliminary analysis highlights how even under strictly regulated markets, firms can still have a significant impact on individual outcomes. These findings are particularly

[7] Another useful path forward would be to compare, where possible, the aggregate variation from the shift-share with the individual level analyses to assess when the shift-share IV leads to biased estimates. This exercise will appear in a future version of this paper.

consequential in a healthcare setting. Governments that leverage private markets to deliver public benefits must also ensure that market participants are delivering services without compromising quality. There are extensions to our analysis we plan to explore. For instance, we have access to individual level enrollment data for a subset of the Colombian population that we link to healthcare utilization information. These data will allow us to explore heterogeneity in plan effects across firms, types of individuals, and markets. These data require further analysis and will feature in a future iteration of this paper. These findings will provide clear guidance for policymakers as they weigh the distributional benefits and consequences of adopting a publicly sponsored privately administered healthcare system in Colombia.

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Tables and Figures

Table 1: Bankruptcy-Municipality Summary Statistics, 2019–2022

Municipalities	Mean (1)	SD (2)	N (3)
Panel A: Recipient EPS			
All	3	2	1,120
Small	3	1	412
Large	4	2	708
Panel B: Δ Market Share			
All	0.123	0.132	1,120
Small	0.174	0.164	412
Large	0.092	0.097	708
Panel C: Δ Alg. Market Share			
All	0.124	0.141	1,120
Small	0.180	0.177	412
Large	0.091	0.101	708
Panel D: Δ Mortality Rate			
All	-0.030	0.207	1,120
Small	-0.041	0.301	412
Large	-0.023	0.123	708
Panel E: Δ Utilization			
All	1.186	8.650	1,112
Small	-0.309	7.743	406
Large	2.045	9.025	706

Notes: This table reports summary statistics for the aggregate data sample of bankruptcy-municipality pairs. The sample includes data on all municipalities that experienced a bankruptcy between 2019–2022. Values are reported for all municipalities, small municipalities, and large municipalities. Small (large) municipalities have a below (above) median population of 9,981 (44,039) affiliates. Panel A reports the average number of surviving EPS firms following a bankruptcy; Panel B reports the observed change in market shares in the month following assignment of impacted affiliates to new EPS plans; Panel C reports the change in market shares predicted by the assignment algorithm used by the Colombian government; Panel D reports the municipality mortality rate per-100,000 affiliates one month following the assignment procedure; Panel E reports the municipality healthcare utilization rate per-100,000 affiliates in thousands of pesos one month following the assignment procedure.

Table 2: Effect of Assignment Algorithm on Market Share Changes Post Bankruptcy, 2019–2022

	All Muni. (1)	Q1 Affil. (2)	Q2 Affil. (3)	Q3 Affil. (4)	Q4 Affil. (5)
Δ Market Share (predic.)	0.922***	0.899***	0.919***	0.940***	0.978***
	(0.007)	(0.014)	(0.014)	(0.009)	(0.016)
Municip.	588	147	147	147	147
Obs.	1120	179	233	287	421
R^2	0.960	0.957	0.943	0.963	0.965
Mean Outcome	0.123	0.194	0.159	0.126	0.069
Aff. cutoff		10,224	21,470	45,189	8,939,870
Aff. p50		6,940	15,386	29,810	148,979

Notes: This table reports estimate of the effect of the change in market shares predicted by the assignment algorithm onto the observed change in market shares following a bankruptcy. The sample includes data on all municipalities that experienced a bankruptcy between 2019–2022. Column (1) pools all municipality-bankruptcy pairs. Columns (2)–(5) use subsets of municipality-bankruptcy pairs based on quartiles of the number of affiliates that reside within a municipality. "Affiliate Cutoff" is the upper bound of the number of affiliates within a quartile. For example, the first quartile in column (2) includes 147 municipalities which have fewer than 10,224 affiliates. "Affiliate Median" denotes the median number of affiliates within the municipalities in the grouping. $***p < 0.01$; $**p < 0.05$; $*p < 0.1$. Standard errors are clustered at the municipality.

Table 3: Effect of Bankruptcies on Municipality Mortality Rate, 2019–2022

	All Muni. (1)	Q1 Affil. (2)	Q2 Affil. (3)	Q3 Affil. (4)	Q4 Affil. (5)
Δ Market Share	-0.111*	0.004	-0.074	-0.085	-0.304***
	(0.065)	(0.126)	(0.159)	(0.078)	(0.095)
Municip.	588	147	147	147	147
Obs.	1120	179	233	287	421
R^2	0.007	.	0.003	0.009	0.055
Mean Outcome	-0.030	-0.074	-0.016	-0.034	-0.016
Aff. cutoff		10,224	21,470	45,189	8,939,870
Aff. p50		6,940	15,386	29,810	148,979

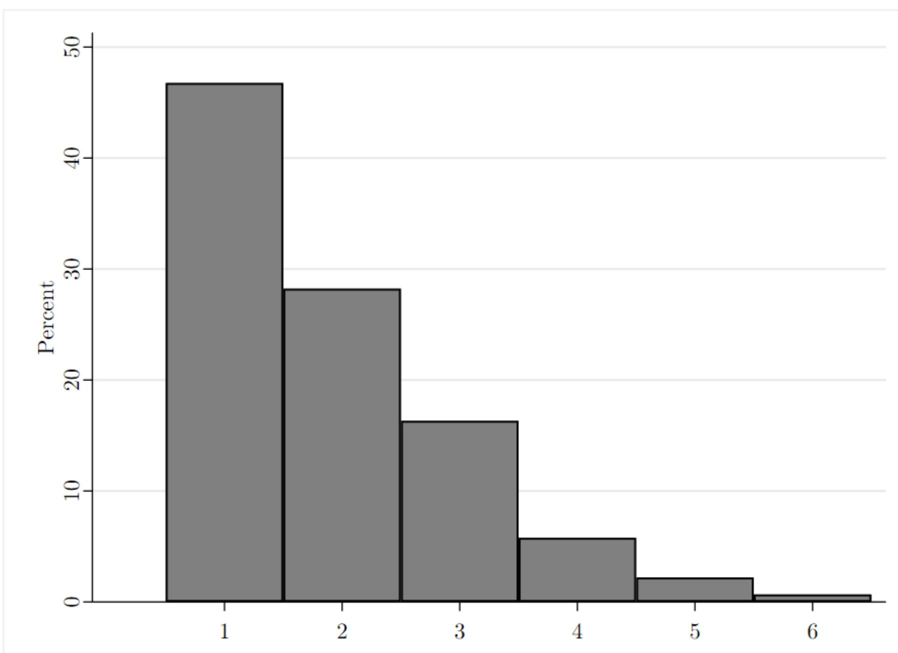
Notes: This table reports IV estimates which regress the morality rate in a municipality onto changes in market shares following a bankruptcy. The first stage instrument is the change in market shares predicted by the assignment algorithm. The mortality rate is measured as the number of deaths per 100,000 affiliates. The sample includes data on all municipalities that experienced a bankruptcy between 2019–2022. Column (1) pools all municipality-bankruptcy pairs. Columns (2)–(5) use subsets of municipality-bankruptcy pairs based on quartiles of the number of affiliates that reside within a municipality. "Affiliate Cutoff" is the upper bound of the number of affiliates within a quartile. For example, the first quartile in column (2) includes 147 municipalities which have fewer than 10,224 affiliates. "Affiliate Median" denotes the median number of affiliates within the municipalities in the grouping. $***p < 0.01$; $**p < 0.05$; $*p < 0.1$. Standard errors are clustered at the municipality.

Table 4: Effect of Bankruptcies on Municipality Healthcare Utilization, 2019–2022

	All Muni. (1)	Q1 Affil. (2)	Q2 Affil. (3)	Q3 Affil. (4)	Q4 Affil. (5)
Δ Market Share	-3.647**	9.493***	-0.248	-6.889*	-17.741***
	(1.526)	(2.565)	(3.357)	(4.128)	(5.962)
Municip.	581	144	144	147	146
Obs.	1112	176	230	286	420
R^2	0.004	0.049	0.000	0.012	0.025
Mean Outcome	1.186	-1.032	0.245	1.703	2.279
Aff. cutoff		10,224	21,470	45,189	8,939,870
Aff. p50		6,940	15,386	29,810	148,979

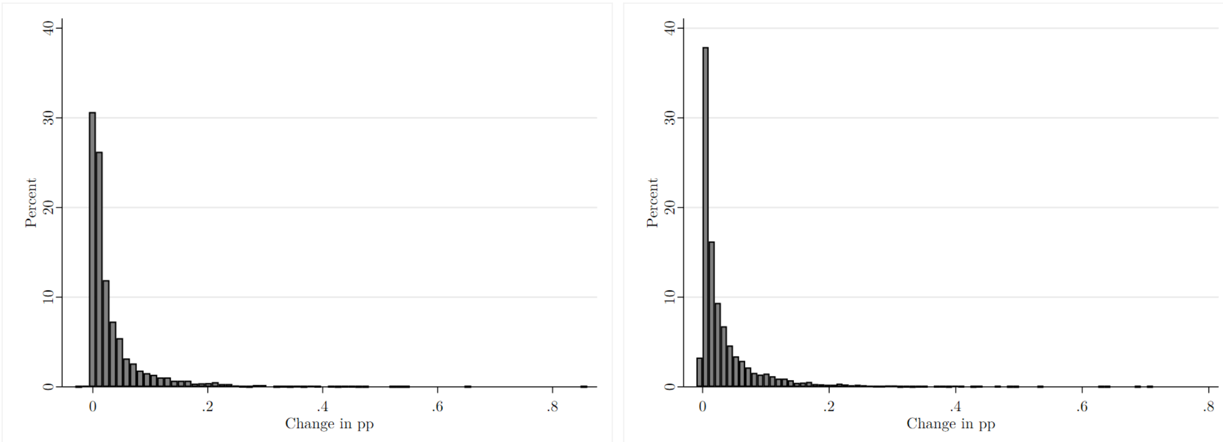
Notes: This table reports IV estimates which regress healthcare utilization within a municipality onto changes in market shares following a bankruptcy. The first stage instrument is the change in market shares predicted by the assignment algorithm. Healthcare utilization is measured from the RIPS data in thousands of pesos per-affiliate. The sample includes data on all municipalities that experienced a bankruptcy between 2019–2022. Column (1) pools all municipality-bankruptcy pairs. Columns (2)–(5) use subsets of municipality-bankruptcy pairs based on quartiles of the number of affiliates that reside within a municipality. "Affiliate Cutoff" is the upper bound of the number of affiliates within a quartile. For example, the first quartile in column (2) includes 147 municipalities which have fewer than 10,224 affiliates. "Affiliate Median" denotes the median number of affiliates within the municipalities in the grouping. $***p < 0.01$; $**p < 0.05$; $*p < 0.1$. Standard errors are clustered at the municipality.

Figure 1: Number of Bankruptcies by Municipality, 2019–2022



Notes: This figure presents the distribution of the number of bankruptcies per municipality in our aggregate and individual samples that occurred between 2019–2022.

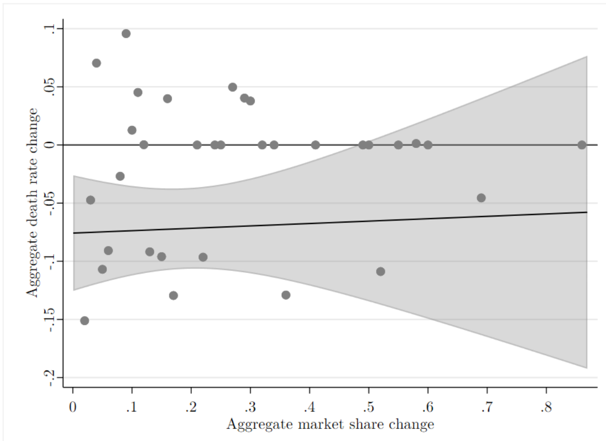
Figure 2: Aggregate Observed and Predicted Market Share Change, 2019–2022



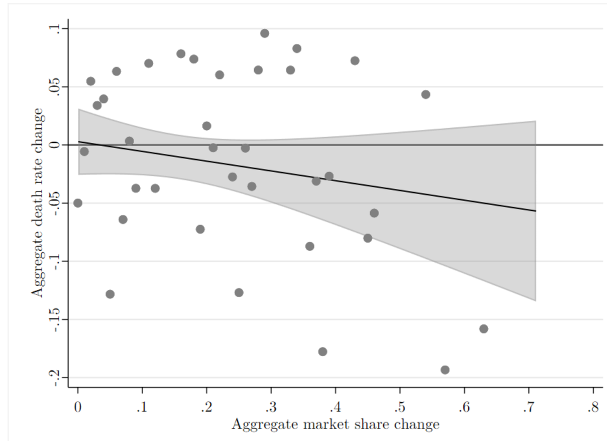
a) Observed **b) Predicted**

Notes: This figure presents the distribution of the changes in EPS market shares following a bankruptcy episode. The left panel reports the distribution of the observed changes in EPS market shares, while the right panel reports the distribution of the change in EPS market shares predicted by the government's assignment algorithm. The sample includes bankruptcy episodes from 2019–2022 and all impacted municipalities.

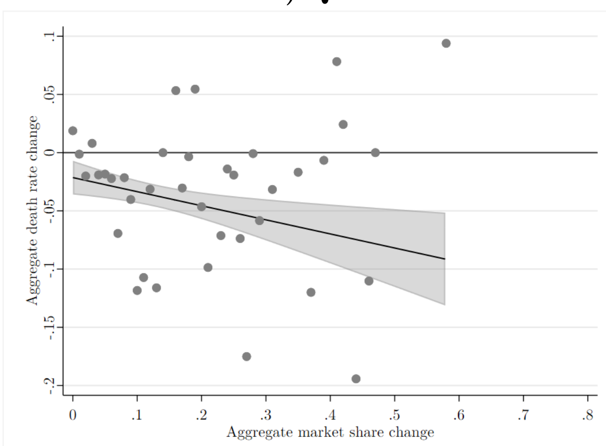
Figure 3: Changes in Market Shares and Municipality Mortality Rates by Municipality Size, 2019–2022



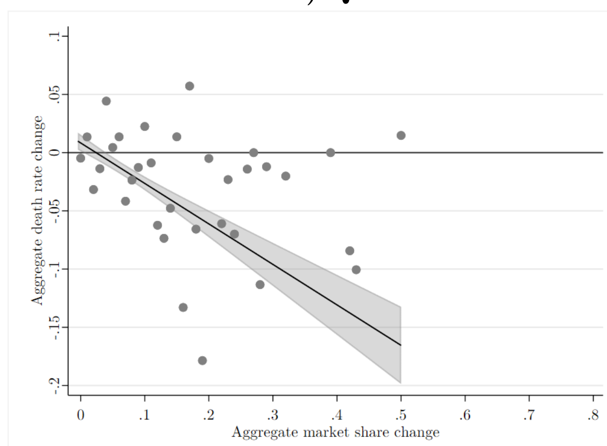
a) Q1



b) Q2



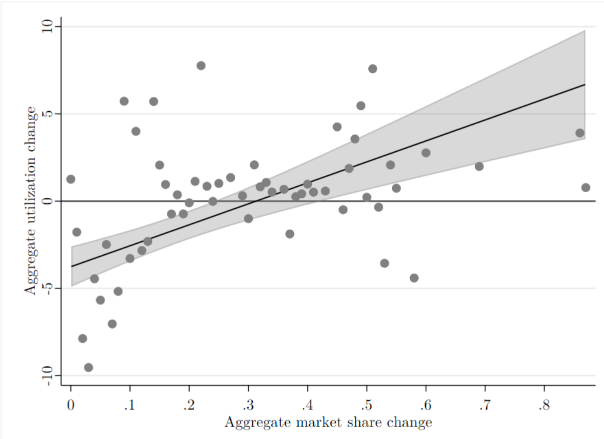
c) Q3



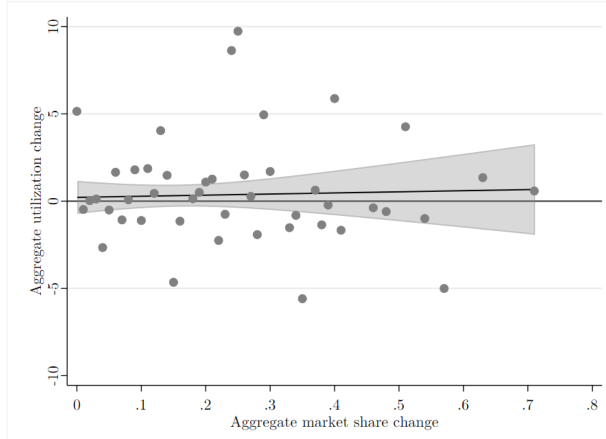
d) Q4

Notes: This figure plots the Lowess smoother to the relationship between changes in market shares and municipality death rate following a bankruptcy. The sample includes bankruptcy episodes from 2019–2022 and is broken into four quartiles based on the number of affiliates that reside within the municipality. The mortality is measured as the number of deaths within a municipality per 100,000 affiliates.

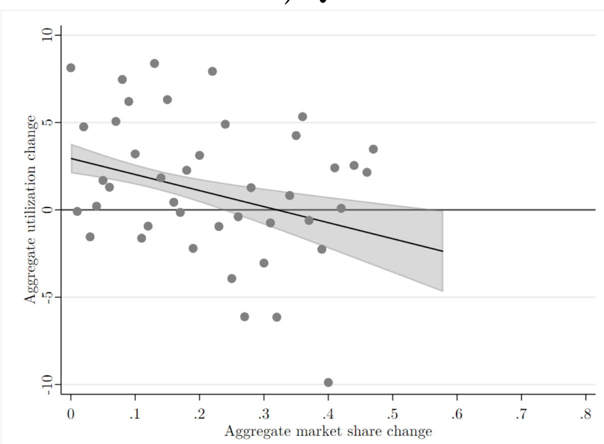
Figure 4: Changes in Market Shares and Municipality Healthcare Utilization by Municipality Size, 2019–2022



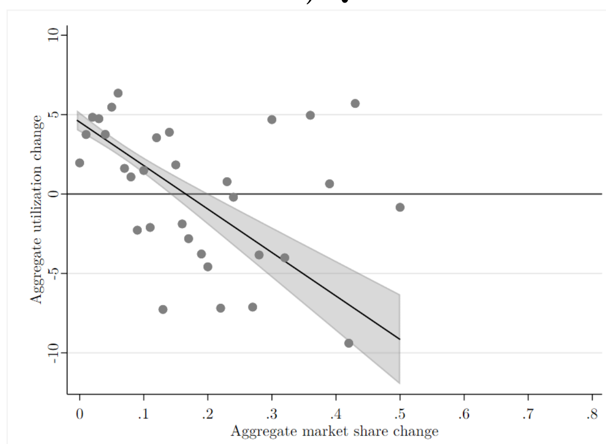
a) Q1



b) Q2



c) Q3



d) Q4

Notes: This figure plots the Lowess smoother to the relationship between changes in market shares and municipality healthcare utilization following a bankruptcy. The sample includes bankruptcy episodes from 2019–2022 and is broken into four quartiles based on the number of affiliates that reside within the municipality. Healthcare utilization is measured from the RIPS data in thousands of pesos per-affiliate.

A Additional Results

Table A1: Effect of Assignment Algorithm on Market Share Changes Post Bankruptcy by EPS, 2019–2022

	All Muni. (1)	Q1 Affil. (2)	Q2 Affil. (3)	Q3 Affil. (4)	Q4 Affil. (5)
Panel A					
EPS A	0.947***	0.971***	0.942***	0.917***	0.989***
	(0.016)	(0.033)	(0.015)	(0.022)	(0.033)
R^2	0.981	0.974	0.989	0.986	0.948
Panel B					
EPS B	0.998***	0.830***	1.052***	0.963***	0.958***
	(0.049)	(0.009)	(0.132)	(0.039)	(0.079)
R^2	0.674	0.993	0.623	0.674	0.869
Panel C					
EPS C	1.191***	1.167***	1.472***	1.223***	1.167***
	(0.187)	(0.253)	(0.505)	(0.174)	(0.075)
R^2	0.523	0.562	0.407	0.636	0.691
Panel D					
EPS D	0.947***	1.065***	0.941***	0.840***	0.874***
	(0.092)	(0.184)	(0.118)	(0.022)	(0.038)
R^2	0.802	0.927	0.778	0.990	0.936
Panel E					
EPS E	1.401***	1.644***	1.179***	1.483***	1.053***
	(0.144)	(0.185)	(0.222)	(0.131)	(0.039)
R^2	0.886	0.957	0.843	0.891	0.925
Panel F					
EPS F	0.905***	0.832***	0.996***	0.975***	1.005***
	(0.070)	(0.135)	(0.025)	(0.035)	(0.032)
R^2	0.888	0.809	0.973	0.946	0.941
Panel G					
EPS G	0.609***	0.443***	0.745***	0.714***	1.047***
	(0.078)	(0.127)	(0.147)	(0.126)	(0.064)
R^2	0.646	0.499	0.733	0.669	0.943
Panel H					
EPS H	0.974***	0.953***	0.990***	0.998***	0.975***
	(0.013)	(0.026)	(0.020)	(0.015)	(0.076)
R^2	0.975	0.992	0.967	0.978	0.942
Panel I					
EPS I	0.875***	0.886***	0.802***	0.992***	0.993***
	(0.048)	(0.032)	(0.113)	(0.014)	(0.098)
R^2	0.869	0.950	0.789	0.970	0.524
Municip.	588	147	147	147	147
Obs.	1120	179	233	287	421
Mean mkt share	0.035	0.078	0.056	0.041	0.015
Aff. cutoff		10,224	21,470	45,189	8,939,870
Aff. p50		6,940	15,386	29,810	148,979

Notes: This table reports estimate of the effect of the change in market shares predicted by the assignment algorithm onto the observed change in market shares for each EPS following a bankruptcy. The sample includes data on all municipalities that experienced a bankruptcy between 2019–2022. Column (1) pools all municipality-bankruptcy pairs. Columns (2)–(5) use subsets of municipality-bankruptcy pairs based on quartiles of the number of affiliates that reside within a municipality. "Affiliate Cutoff" is the upper bound of the number of affiliates within a quartile. For example, the first quartile in column (2) includes 147 municipalities which have fewer than 10,224 affiliates. "Affiliate Median" denotes the median number of affiliates within the municipalities in the grouping. $***p < 0.01$; $**p < 0.05$; $*p < 0.1$. Standard errors are clustered at the municipality.

Table A2: Effect of Bankruptcies on Municipality Mortality Rate by EPS, 2019–2022

	All Muni. (1)	Q1 Affil. (2)	Q2 Affil. (3)	Q3 Affil. (4)	Q4 Affil. (5)
EPS A	-0.303	-0.281	-0.365	0.420	-0.127
	(0.272)	(0.583)	(0.486)	(0.308)	(0.888)
EPS B	-0.186	0.862	0.198	-0.284	-1.311
	(0.451)	(1.406)	(1.128)	(0.437)	(0.798)
EPS C	-0.316	0.137	-1.189	-0.182	-0.165
	(0.222)	(0.244)	(0.739)	(0.399)	(0.421)
EPS D	3.032***	-12.399***	4.066***	2.775**	1.771
	(0.910)	(3.751)	(1.169)	(1.178)	(1.332)
EPS E	-0.192	-0.291*	-0.243	-0.011	1.092***
	(0.147)	(0.169)	(0.347)	(0.401)	(0.383)
EPS F	-0.407	0.918	-1.401**	-0.924**	0.000
	(0.730)	(1.556)	(0.595)	(0.407)	(0.878)
EPS G	-0.469*	-0.699	-0.564	-0.278	-0.629**
	(0.247)	(0.471)	(0.526)	(0.269)	(0.270)
EPS H	0.639***	1.457***	0.693	-0.192	0.370
	(0.222)	(0.376)	(0.549)	(0.403)	(0.554)
EPS I	0.443**	0.975***	0.511	0.066	0.346
	(0.220)	(0.376)	(0.523)	(0.271)	(0.482)
Municip.	588	147	147	147	147
Obs.	1120	179	233	287	421
R^2	0.018	0.067	.	0.035	0.048
Mean Outcome	-0.030	-0.074	-0.016	-0.034	-0.016
Aff. cutoff		10,224	21,470	45,189	8,939,870
Aff. p50		6,940	15,386	29,810	148,979

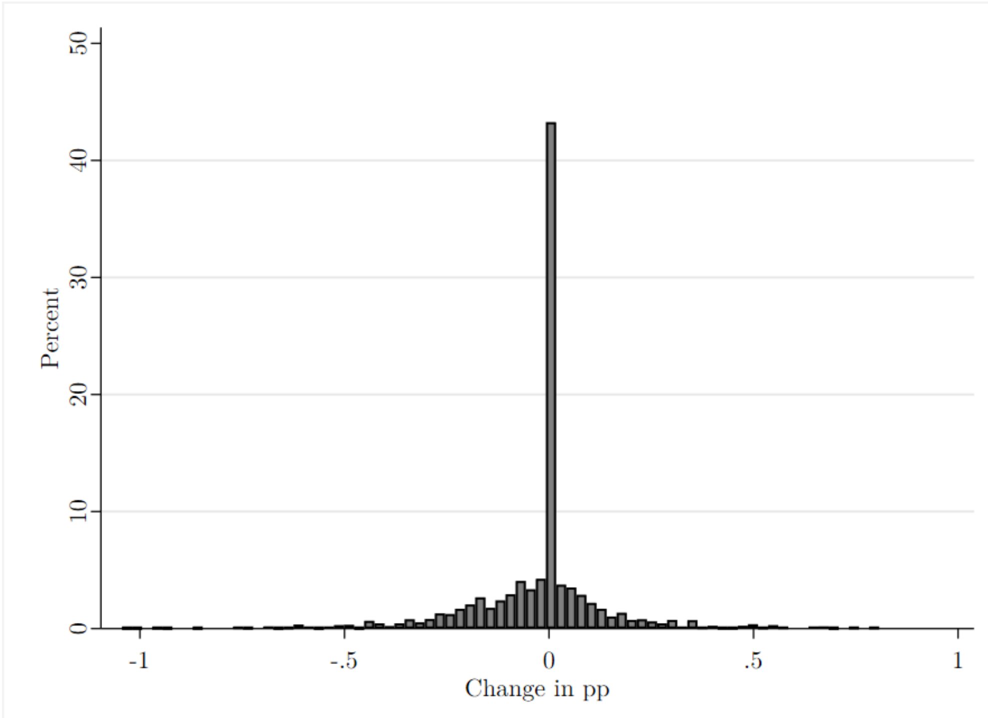
Notes: This table reports IV estimates which regress the morality rate in a municipality onto changes in market shares following a bankruptcy. The first stage instrument is the change in market shares predicted by the assignment algorithm for each EPS in a municipality. The mortality rate is measured as the number of deaths per 100,000 affiliates. The sample includes data on all municipalities that experienced a bankruptcy between 2019–2022. Column (1) pools all municipality-bankruptcy pairs. Columns (2)–(5) use subsets of municipality-bankruptcy pairs based on quartiles of the number of affiliates that reside within a municipality. "Affiliate Cutoff" is the upper bound of the number of affiliates within a quartile. For example, the first quartile in column (2) includes 147 municipalities which have fewer than 10,224 affiliates. "Affiliate Median" denotes the median number of affiliates within the municipalities in the grouping. $***p < 0.01$; $**p < 0.05$; $*p < 0.1$. Standard errors are clustered at the municipality.

Table A3: Effect of Bankruptcies on Municipality Healthcare Utilization by EPS, 2019–2022

	All Muni. (1)	Q1 Affil. (2)	Q2 Affil. (3)	Q3 Affil. (4)	Q4 Affil. (5)
EPS A	-1.737	-11.257	23.749***	-1.888	-43.353
	(6.830)	(16.613)	(7.856)	(16.098)	(51.385)
EPS B	-35.523*	-19.251	-8.237	-42.752**	-66.170
	(18.659)	(39.461)	(40.831)	(20.979)	(43.730)
EPS C	-21.032**	1.334	-33.726	-8.614	-81.093***
	(9.704)	(8.555)	(26.943)	(29.585)	(31.431)
EPS D	14.034	120.110	31.834*	2.210	108.253
	(17.671)	(182.148)	(16.392)	(51.656)	(128.870)
EPS E	-5.756	8.957**	-3.743	-35.038**	-40.294
	(4.462)	(3.846)	(10.655)	(14.489)	(34.216)
EPS F	-2.153	24.740	19.419	2.522	-142.667**
	(9.223)	(18.083)	(18.136)	(28.550)	(55.528)
EPS G	-0.456	26.885**	-10.622*	-2.573	0.703
	(4.652)	(12.209)	(6.281)	(12.849)	(20.096)
EPS H	26.590**	45.065***	13.226	22.084	38.388
	(10.981)	(14.624)	(34.477)	(18.927)	(42.154)
EPS I	-9.589***	2.319	3.464	-19.806	21.707
	(3.363)	(4.954)	(4.967)	(12.690)	(36.585)
Municip.	581	144	144	147	146
Obs.	1112	176	230	286	420
R^2	0.011	0.027	0.027	0.028	0.050
Mean Outcome	1.186	-1.032	0.245	1.703	2.279
Aff. cutoff		10,224	21,470	45,189	8,939,870
Aff. p50		6,940	15,386	29,810	148,979

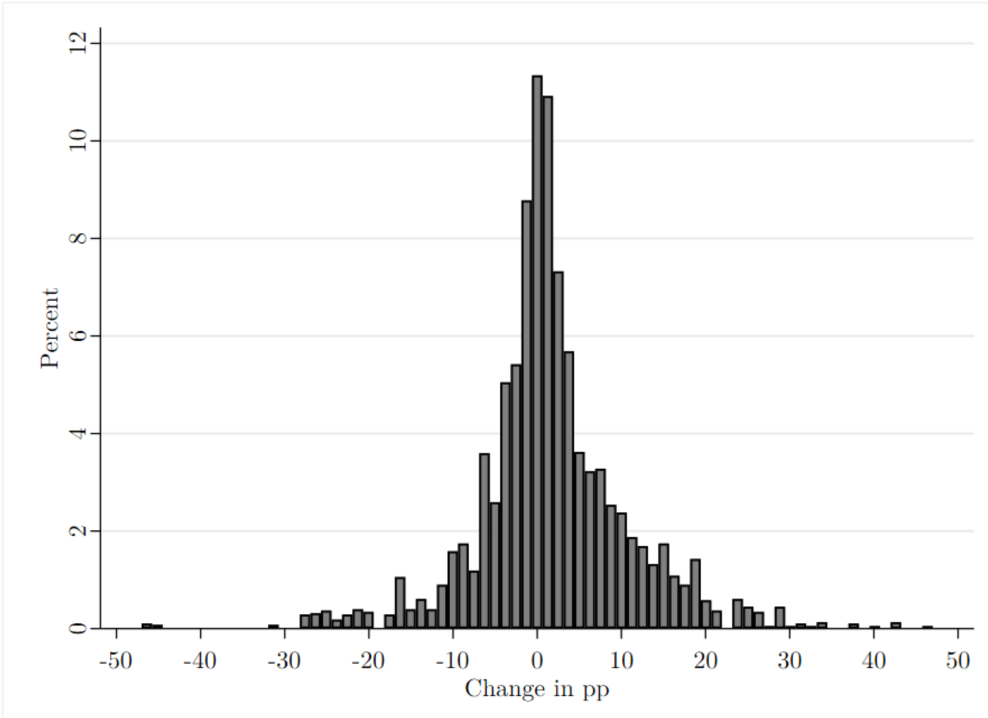
Notes: This table reports IV estimates which regress healthcare utilization within a municipality onto changes in market shares following a bankruptcy. The first stage instrument is the change in market shares predicted by the assignment algorithm for each EPS in a municipality. Utilization is measured from the RIPS data in thousands of pesos per-affiliate. The sample includes data on all municipalities that experienced a bankruptcy between 2019–2022. Column (1) pools all municipality-bankruptcy pairs. Columns (2)–(5) use subsets of municipality-bankruptcy pairs based on quartiles of the number of affiliates that reside within a municipality. "Affiliate Cutoff" is the upper bound of the number of affiliates within a quartile. For example, the first quartile in column (2) includes 147 municipalities which have fewer than 10,224 affiliates. "Affiliate Median" denotes the median number of affiliates within the municipalities in the grouping. $***p < 0.01$; $**p < 0.05$; $*p < 0.1$. Standard errors are clustered at the municipality.

Figure A1: Change in Municipality Mortality Rate Distribution, 2019–2022



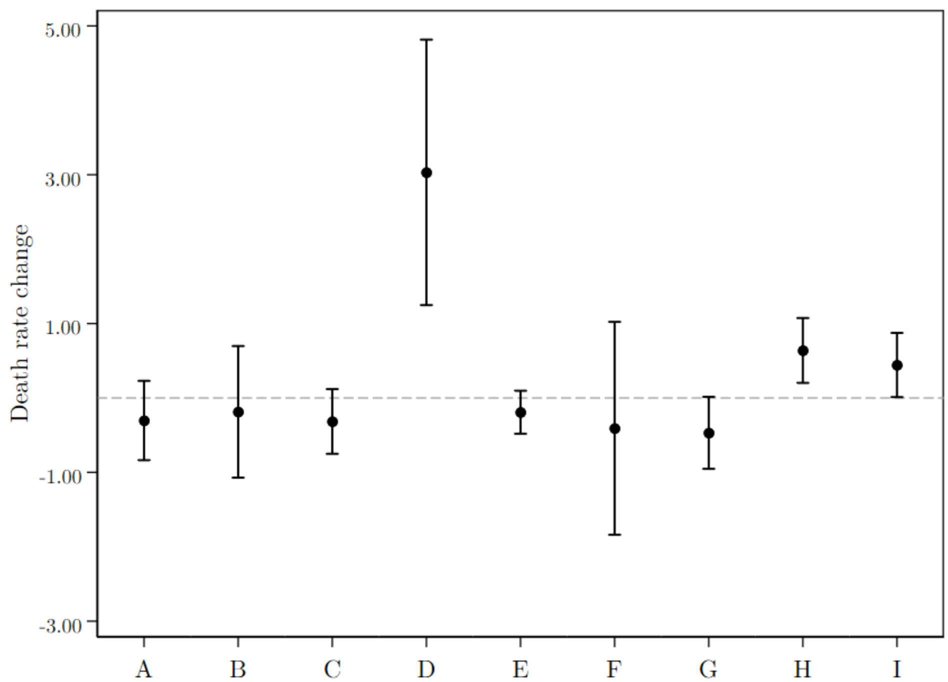
Notes: This figure presents the distribution of the change in the municipality death rate one month before and after a reassignment process due to a bankruptcy event. The sample includes all municipalities that experienced a bankruptcy between 2019–2022. The mortality rate is measured per 100,000 affiliates in a municipality.

Figure A2: Change in Municipality Healthcare Utilization Rate Distribution, 2019–2022



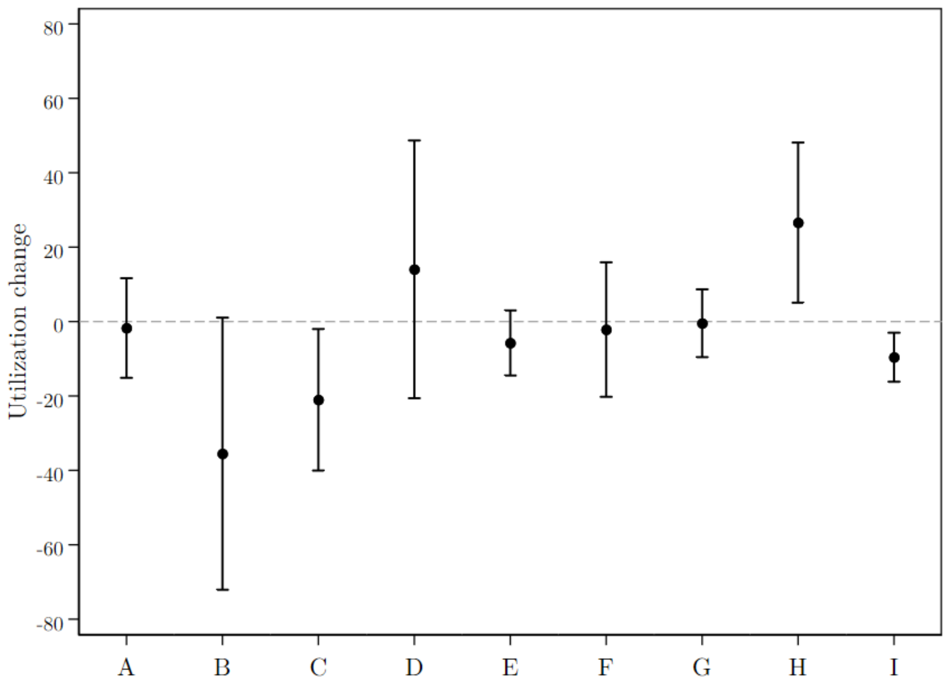
Notes: This figure presents the distribution of the change in the municipality healthcare utilization rate one month before and after a reassignment process due to a bankruptcy event. The sample includes all municipalities that experienced a bankruptcy between 2019–2022. Healthcare utilization is measured in thousands of pesos per-affiliate in a municipality.

Figure A3: Aggregate Sample Second Stage: Effect of Bankruptcies on Municipality Mortality Rate by EPS, 2019–2022



Notes: This figure plots the IV coefficient estimates which regress the morality rate in a municipality onto changes in market shares following a bankruptcy. The first stage instrument is the change in market shares predicted by the assignment algorithm for each EPS in a municipality. The mortality rate is measured as the number of deaths per 100,000 affiliates. The sample includes data on all municipalities that experienced a bankruptcy between 2019–2022. The underlying estimates are presented in Table A2.

Figure A4: Aggregate Sample Second Stage: Effect of Bankruptcies on Municipality Healthcare Utilization by EPS, 2019–2022



Notes: This figure plots the IV coefficient estimates which regress the healthcare utilization rate in a municipality onto changes in market shares following a bankruptcy. The first stage instrument is the change in market shares predicted by the assignment algorithm for each EPS in a municipality. The mortality rate is measured as the number of deaths per 100,000 affiliates. The sample includes data on all municipalities that experienced a bankruptcy between 2019–2022. The underlying estimates are presented in Table A3.

B Healthcare Utilization Metric

In this section we describe how we construct the measure of healthcare utilization used in our empirical analysis.

B.1 Inputs

Health care procedures

1. **CUPS code dictionary:** Unique codes of health procedures (CUPS) from the Ministry of Health data warehouse (RIPS) between 2009–2021. It includes 11,964 different highly detailed procedures.

Reference prices

1. **Official 2020 SOAT codes rate manual:** Public rate manual, released by the government each January, which includes 3,214 different procedure codes. Of which 1,443 have a specific price, and the remaining 1,771 procedures have a corresponding surgical group. They are interventions that, due to their level of complexity, require highly specialized resources for their execution. Each of the 16 groups, also has a price. We use 2020 rates since is the most updated manual before the COVID-19 pandemic.

2. **2020 Sufficiency study:** Each December, the Ministry of Health releases an annual analysis for the following year. It aims to determine the adequacy of the budget insurers receive per member, to fund the services of the health plans. It includes prices reported by insurers for most of the procedures which we use as the last resource to complete missing rates. We use 2020 rates since it is also the latest study before the pandemic and correspond to the SOAT period.

Crosswalks

1. **Public crosswalk:** This healthcare procedure crosswalk released by the independent site *NormasSalud*, relates the official Ministry of Health CUPS code, with their homologous code in the reference price manual SOAT. In this manual 3,228 SOAT codes, correspond to 2,650 CUPS codes. [8]

2. **Insurer crosswalk:** External SOAT-CUPS crosswalk of the (feature) health insurer. This database includes 2,638 SOAT codes that correspond to 8,702 CUPS codes.

3. **Insurer's rate manual:** External crosswalk and rate manual of the (feature) health insurer. This database contains 2,606 SOAT codes that correspond to 8,729 CUPS codes and 582 rates. Then, it works as crosswalk and price manual that commonly uses SOAT rates. This insurer uses it when some situations require registering a standard price.

[8] To find the latest SOAT-CUPS public crosswalk visit: https://www.normassalud.com/

B.2 Procedure

We aim to create an exhaustive crosswalk between the health procedure codes and their homologous SOAT rate. For this, we combine all different crosswalks for official SOAT codes. In a few cases, we average them with the insurer rates and proceed to complement missing rates with the Sufficiency study.

1. We start by taking a total of 11,964 CUPS codes of different healthcare procedures from the Ministry's data warehouse and matching them with SOAT 2020 codes. For each crosswalk, there is one way to assign a SOAT 2020 rate to each CUPS code (using the public source or the insurer source). We take the average of the corresponding rates to generate a unique rate by CUPS using the SOAT manual. We obtain 1,411 rates for 10,122 CUPS procedures.

2. We have rates for both the insurer and SOAT's manual in 7,694 cases of CUPS codes. Where 1,701 rates differ from each other with mean of 429,409 COP and standard deviation of 600,441 COP. While the mean and standard deviation of all SOAT rates is 1,490,506 and 1,190,081, respectively. For such cases we average the previous SOAT with the insurer rates to induce more variability. Then, we obtain 1,883 different rates for the previous 10,122 CUPS procedures.

3. To complete some of the 1,842 missing rates of the CUPS codes, we match existing procedures rates to others with similar names but that have no rate. This way, we determine a rate for 10,748 CUPS codes in total.

4. Next, we use the Sufficiency study rates for 274 additional CUPS without rates.

5. Finally, we repeat the process in step (3) for procedures that only have rates from the sufficiency study, and we find a rate for another 33 CUPS codes.

Note: We end up with a database with 11,055 different code CUPS with a reference price that corresponds to 2,243 rates. Which represents 93%, 94% and 95% of CUPS codes that appear in the Ministry of Health data warehouse for at least one, two, and three years respectively.