Incentives for health care quality:
Evidence from the dialysis market in Uruguay

Rodrigo Surraco Williman

Programa de Maestría en Economía de la Facultad de Ciencias Económicas y de Administración

Universidad de la República

Montevideo, Uruguay

Diciembre de 2024

Incentives for health care quality:
Evidence from the dialysis market in Uruguay

Rodrigo Surraco Williman

Tesis de Maestría presentada al Programa de Maestría en Economía de la Facultad de Ciencias Económicas y de Administración, Universidad de la República, como parte de los requisitos para la obtención del título de Magíster en Economía.

Directores de tesis:

Prof. Rodrigo Ceni

Prof. Sebastián Fleitas

Director académico:

Prof. Rodrigo Ceni

Montevideo, Uruguay

Diciembre de 2024

FACULTAD DE CIENCIAS ECONÓMICAS Y DE ADMINISTRACIÓN
DEPARTAMENTO DE ECONOMÍA
UNIVERSIDAD DE LA REPÚBLICA URUGUAY

Página de aprobación

El tribunal docente integrado por los abajo firmantes aprueba el Trabajo Final:

Título

Incentives for health care quality: Evidence from the dialysis market in Uruguay

Autor

Rodrigo Surraco Williman

Tutores

Prof. Rodrigo Ceni

Prof. Sebastián Fleitas

Posgrado

Maestría en Economía

Puntaje

____

Tribunal

Profa. Paula Carrasco

Prof. Igal Hendel

Profa. Tatiana Rosá

Fecha: 20 de diciembre de 2024

Agradecimientos

Agradezco especialmente a mis tutores, Rodrigo Ceni y Sebastián Fleitas, por la guía, la generosidad y la confianza incansables. Sin su orientación este trabajo no hubiera sido posible. Agradezco en ellos a la Universidad de la República, por ser comunidad académica rigurosa y fraterna, por construir vocación y compromiso.

Agradezco a los nefrólogos Alejandro Ferreira, Ricardo Silvariño y, sobre todo, Alejandro Opertti, por compartir su conocimiento sobre el tratamiento dialítico y el funcionamiento del sistema de salud uruguayo. A Pablo Blanchard y Rodrigo González Valdenegro, por sus aportes sobre la metodología utilizada. A los docentes de la maestría Cecilia Parada y Gonzalo Salas, por sus comentarios en los comienzos de este proyecto. A Lucía Bertoletti, por discusiones imprescindibles. A Alicia Ferreira, por proporcionar información importante sobre los datos. A Mariela Garau, Gustavo Saona y Santiago Torales, por sus comentarios sobre el uso de variables médicas. A la Asociación de Transplantados del Uruguay, especialmente a José Fernández, Natalia Fernández, Aldana Marrero y Diego Sotelo, por compartir su trabajo y sus valiosas experiencias. A Javier Bonetti, Gustavo Bonetti, Virginia Matonte, María Ana Porcelli, Pablo Presso y Verónica Risso, por proporcionar información clave sobre la diálisis en Uruguay. A Ignacio González, Hugo Ñopo y Lulu Wang, por abrirme horizontes. A Guille, Joaco, Nacho, Martín, Maru, Paula y Rodri, por hacer de la maestría una experiencia mucho más linda. A María y Nano, por el aguante. A mi familia, especialmente a mis padres y la Abía, por el apoyo y amor incondicional. A Lulita, por ser mi casa.

Agradezco al Programa de Becas de la Maestría en Economía y a la Agencia Nacional de Investigación e Innovación, por el apoyo financiero. Al Fondo Nacional de Recursos, por proporcionar los datos necesarios para esta investigación

Todos los errores son de mi responsabilidad.

Incentives for health care quality:
Evidence from the dialysis market in Uruguay

Rodrigo Surraco Williman*

Abstract

In publicly funded health systems, reimbursement often fails to reflect care quality, creating a principal-agent problem in which providers determine quality levels unobserved by both patients and payers. This paper studies how financial incentives affect provider behavior in Uruguay's dialysis sector, where treatments are fully government-funded, prices are fixed, and quality varies widely across facilities. Using administrative data and a structural model of patient demand and provider behavior, I estimate risk-adjusted quality scores, facility-level marginal costs, and the elasticity of demand for quality. I find that patients place relatively low weight on quality, likely due to information frictions, and that higher quality is costly to provide. Simulations of equilibrium counterfactuals show that a pay-for-performance contract would increase treatment quality by 27 percentage points (36%), reduce government expenditure by 3.3%, and lower provider markups from 23.2% to 6.4%. Combining this policy with reduced information frictions on the demand side yields the same improvements with even higher savings. The findings highlight the potential of incentive-compatible reimbursement schemes to improve both efficiency and patient outcomes in publicly-funded health care markets.

Keywords: health care markets, pay for performance, discrete choice models, information frictions

JEL Codes: L11, L15, I11, I15, I18

Resumen

En los sistemas de salud financiados públicamente, el pago a los prestadores a menudo no depende de la calidad del tratamiento, generando un problema de principal-agente en el que los prestadores determinan niveles de calidad no observados por pacientes ni financiadores. Este artículo estudia cómo los incentivos financieros afectan el comportamiento de los prestadores en el sector de diálisis de Uruguay, donde los tratamientos son totalmente financiados por el gobierno, los precios están fijados administrativamente, y la calidad varía considerablemente entre prestadores. Utilizando datos administrativos y un modelo estructural de demanda de tratamiento y comportamiento de los prestadores, estimo una medida de calidad ajustada por riesgo, costos marginales a nivel del prestador y la elasticidad de la demanda respecto a la calidad. Encuentro que los pacientes asignan un peso relativamente bajo a la calidad, probablemente debido a fricciones informativas, y que proporcionar mayor calidad es costoso para los prestadores. Simulaciones contrafactuales de equilibrio muestran que un contrato de pago por desempeño (pay-for-performance) incrementaría la calidad del tratamiento en 27 puntos porcentuales (36%), reduciría el gasto público en 3,3% y bajaría los márgenes de los prestadores del 23,2% al 6,4%. Combinar esta política con una reducción en las fricciones informativas del lado de la demanda genera las mismas mejoras con ahorros aún mayores. Estos resultados muestran el potencial de los esquemas de pago compatibles con incentivos para mejorar tanto la eficiencia como los resultados de salud de los pacientes en mercados de salud de financiamiento público.

Palabras clave: mercados de salud, pay for performance, modelos de elección discreta, fricciones de información

Códigos JEL: L11, L15, I11, I15, I18

*Northwestern Kellogg. Email: rodrigo.surraco@kellogg.northwestern.edu. Actualizado el 1ero de junio de 2025.

1 Introduction

In publicly funded health systems, provider reimbursement is often decoupled from care quality. This creates a classic principal-agent problem: while regulators pay for treatments, facilities determine quality—often unobserved by either patients or payers. When information frictions and regulated prices prevail, as in the dialysis sector, providers may underinvest in quality, and public funds may be misallocated[1]. This is especially a problem in developing countries, where the incidence of chronic diseases is on the rise because of population aging.

This paper studies how financial incentives affect provider behavior in the Uruguayan dialysis market, where treatments are fully government-funded (at $90.5 million annually) and prices are fixed[2]. Despite universal access, there is substantial heterogeneity in treatment quality across facilities[3]. Using rich administrative data and a structural model of patient demand and facility behavior, I ask: What is the cost of quality provision, and how would a pay-for-performance contract alter equilibrium quality and government spending?

I begin by quantifying facility quality using URR adequacy—a measure strongly correlated with survival[4]. I estimate risk-adjusted quality scores that isolate the contribution of facilities to patient health, following the approach in Einav et al. (2018). I use these scores to estimate a demand model for facility choice based on a two-step procedure that mirrors Berry et al. (2004) and accounts for the unobservable restriction of the choice set due to facility congestion (Eliason, 2022). With demand estimates in hand, I estimate facilities' marginal costs and the effect of quality on marginal costs using an instrumental variable approach.

I document there is low demand for quality in comparison to other drivers of demand, such as proximity to the facility, which may arise from information frictions. Hence, the willingness to travel for quality is low. Assuming full information, in exchange for a 1km decrease in distance, a patient is willing to give up 15.9 percentage points in the probability of receiving an adequate treatment. I find quality provision is costly, which could further explain why there is low observed quality in some facilities: the cost of quality represents 31.8% of the mean marginal cost. The mean markup is 23.2% of the

[1] In particular, information frictions about quality can drive down optimal quality supply, in detriment of patients (Dranove and Satterthwaite, 1992).

[2] Chronic kidney disease imposes a substantial financial burden worldwide, particularly on low-income populations and public health systems (Jamison, 2018; Francis et al., 2024). In Latin America, its prevalence is projected to more than double between 2016 and 2050 (Chesnaye et al., 2024), with patients often requiring dialysis—a treatment that typically involves four-hour sessions, three times per week.

[3] Figure A1 shows the distribution of multiple quality measures across facility-years; while in some facility-years the percentage of adequate treatments in terms of Urea Reduction Rate (URR) is below 50%, other facility-years achieve near 100%.

[4] URR adequacy increases life expectancy after diagnosis by 8.5 months (22.9%) in my sample.

marginal cost, in line with previous findings for the US (Eliason, 2022).

Using these estimates, I simulate equilibrium counterfactual policies to evaluate the effects of alternative reimbursement and demand-side interventions. I find that a well-calibrated pay-for-performance (P4P) contract can raise average treatment quality by 27 percentage points (36%) while simultaneously reducing government expenditure by 3.3%—equivalent to approximately $2.9 million annually, based on Uruguay's 2017 dialysis spending of $90.5 million. This improvement is achieved under a contract with a base price well below the current flat rate and a relatively steep quality premium, which increases the marginal return to quality provision. As a result, provider markups decline from 23.2% to 6.4%, reflecting reduced rent extraction and a reallocation of surplus toward patients.

To explore the role of information frictions on the demand side, I simulate a setting where patient demand for quality is doubled. Without any change to reimbursement policy, this shift in preferences induces providers to deliver equivalent quality gains due to stronger competitive pressure, and markups fall to 10.1%. This highlights the potential of non-price policies, such as public reporting or quality disclosure, to drive efficiency. I also consider a combined policy where higher patient demand is paired with a P4P scheme. This joint intervention results in equivalent quality gains at a lower price than standalone P4P, as the higher demand allows for a lower quality premium.

Finally, I examine a scenario in which the government mandates perfect quality as a regulatory standard and sets a uniform reimbursement price equal to the maximum observed marginal cost. This policy achieves full quality at the lowest average price among all scenarios, with the average markup falling to just 0.93% of the marginal cost.

The economic discipline has recently made important progress in empirically understanding the effect of incentives on the quality of health care supply (Einav et al., 2018; Hackmann, 2019; Fleitas, 2020) in the context of health insurance choice (Handel and Kolstad, 2015; Vatter, 2022; Handel et al., 2024) and health care provider choice (Eliason, 2022; Cheng, 2023). At the same time, a burgeoning strand of the literature has studied the case of the dialysis industry, leveraging a setting with very precise data on quality (Dai and Tang, 2015; Eliason et al., 2020; Gaynor et al., 2023; Wollmann, 2020; Agarwal and Somaini, 2022; Bertuzzi et al., 2023; Eliason et al., 2024).

This paper makes two contributions to this literature. First, it evaluates a pay-for-performance scheme in the dialysis sector for the first time, complementing closely related work such as Eliason (2022) on U.S. dialysis reimbursement and Camarda (2022) on pay-for-performance in England's hip-replacement market[5].

[5] Eliason (2022) studies the effect of increasing the reimbursement rate on quality in the US dialysis market, finding a positive effect on patient survival, even when holding market structure fixed. Camarda (2022) studies the welfare effect of quality-based prices in the hip-replacement market in England, and

Second, this paper is the first to provide evidence on the cost of and demand for dialysis quality in a developing country. Developing countries need better dialysis care[6], yet studying dialysis markets in developing contexts is particularly challenging: usually, supply is severely limited, and large numbers of patients die prematurely due to lack of access. As a result, it is often impossible to observe equilibrium demand or supply, complicating efforts to analyze market behavior or evaluate policy interventions. Uruguay presents a rare and valuable exception. While still a developing country, it maintains universal public coverage for dialysis and collects rich administrative data across providers (González-Bedat et al., 2020). This setting enables the empirical analysis of demand, cost, and incentives in a way that is typically infeasible in lower-resource environments.

The rest of the paper is structured as follows. Section 2 describes the fundamental features of the dialysis market in Uruguay and its regulation, as well as the effect of treatment quality on survival. Section 3 highlights the most relevant literature on dialysis market structure and incentive mechanisms. Section 4 presents a theoretical framework for dialysis demand and supply, in which patients choose facility based on a number of facility attributes (including quality) to maximize utility and facilities choose their quality to maximize profits. Section 5 section presents the data used. Section 6 explains the empirical strategy employed in order to recover quality scores, estimate demand and back out marginal costs. Section 7 presents the results of this strategy and Section 8 computes counterfactual equilibrium results. Section 9 concludes.

2 Context

2.1 Chronic dialysis treatment

The kidneys primarily perform two functions: they filter waste and toxins from the blood, and they stimulate the production of red blood cells (Eliason et al., 2020). To survive, patients with chronic kidney disease need chronic dialysis treatment or a kidney transplant. Chronic dialysis treatment can be performed in two ways. The first and most common is hemodialysis, a procedure that circulates blood through an external artificial kidney and is generally performed in facilities (within a hospital or not) on an outpatient basis. The second method, peritoneal dialysis, uses cleansing fluid to collect waste and can be performed by the patient at home. Patients are often not given the option to enter peritoneal dialysis due to clinical contraindications, older age, living alone or disability; aditionally, they need adequate home infrastructure for this modality (Lee et al., 2008).

concludes that this alternative payment scheme could close 37% of the gap between current and optimal welfare.

[6]Most of the annual 2 million estimated deaths due to untreated renal disease come from the developing world (Liyanage et al., 2015). In Latin America, over 10% of countries are unable to provide treatment for the majority of patients (Bello et al., 2024).

Although kidney transplant is considered a more appropriate option than dialysis, few patients access it, either due to not being medically fit or due to the low availability of kidneys (Eliason et al., 2020).

The most important quality measure in hemodialysis is the URR, which measures the proportion of urea removed from the body during a dialysis treatment (Eliason, 2022), with a threshold of 0.65. This threshold is often referred to as “dialysis adequacy” by the National Kidney Foundation (Foundation, 2015). Providers have a direct effect on the URR of patients, as URR depends on the quality of inputs like filters and dialysis machine, as well as the human capital of nurses and doctors and the amount of time in treatment. An URR above 0.60 is generally accepted to be correlated with lower mortality (Owen et al., 1993).

Another measure often used to measure dialysis dosage is Kt/V, which compares the amount of fluid that passes through the dialyzer with the amount of fluid in the patient's body. Kt/V will be higher for patients who approach a dialysis session in a worse initial state (CDC, 2009).

Other quality indicators measure the rate of negative outcomes, as performing chronic dialysis treatment can generate different complications. Among the most common are infections of different types, specially septic infections. The level of cleanliness of the establishments and the reutilization of dialyzers usually determine to a large extent the incidence of infections in a facility (Grieco and McDevitt, 2017). The rate of complications, septic infections and survival have been used to measure quality in the literature on the industrial organization of dialysis care (Grieco and McDevitt, 2017; Eliason, 2022; Eliason et al., 2024).

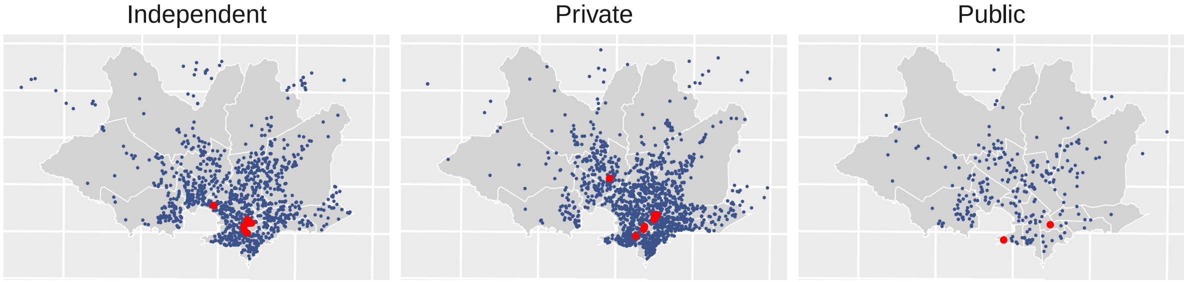
As often happens in various medical conditions, there are higher chronic kidney disease risk factors among the poor, related to non-treatment at early stages, poorly treated diabetes, lack of adherence to medication and bad diet. Conversely, dialysis also makes people more economically vulnerable, mainly because such a time-consuming treatment and poor health make it harder to maintain a full-time job. There are also factors non-related to economic status that play a role in entry to dialysis, such as genetic background and age[7].

2.2 Uruguayan setting

In Uruguay, 2,496 patients were in chronic hemodialysis treatment in 2017 (the last year of my analysis), while 238 people were treated with peritoneal dialysis (González-Bedat

[7]The socioeconomic bias of risk factors in this setting has been emphasized by multiple consulted nephrologists.

Figure 1: Patient and facility location by facility type



Note: Patients entering dialysis 2003-2017 in Montevideo, the Capital city. Red dots represent facilities location, blue dots represent patients' homes. "Private" represents facilities owned by private insurance companies. "Independent" represents private facilities non-associated with insurance companies. "Public" represents public facilities. See Table 1 for a full list of facilities and shares.

et al., 2020). 15% of hemodialysis patients and 40% of peritoneal dialysis patients were on the waiting list for kidney transplant (González-Bedat et al., 2020). In this work I focus on hemodialysis, due to its most widespread use.

The National Resources Fund (FNR) covers all dialysis treatments carried out in Uruguay since 1981 and sets, jointly with the Ministry of Public Health (MSP), the reimbursement (or price)[8] charged by facilities for each hemodialysis session (FNR, 2020). This coverage also includes some medication essential for some patients during treatment[9]. The treatment is provided by Institutes of Highly Specialized Medicine (IMAE), public and private facilities that perform highly complex and costly procedures (Law 16,343). These institutions are legally separate from health insurance and providers.

Facilities (IMAEs) can be classified as "public", "private" or "independent". Figure 1 shows the location of these facilities by type, and their patients.

Private facilities are owned by a private health insurance. Private health insurance and health care providers in Uruguay have been historically vertically integrated. They are funded by the National Health Fund (FONASA) government program in the case of formal employees, retirees and their dependents, and through individual premiums otherwise. Patients not covered by FONASA can access a public health insurance/provider with minimum out-of-pocket spending and no premium[10]. These public and private health care organizations must re-insure their patients against "catastrophic" (high cost) health episodes through the FNR (Fleitas, 2017). Private insurance/providers have non-profit status, meaning they cannot deliver utilities to their owners.

[8]The regulated price has remained stable since 2009, in real terms (around 180 dollars per session).

[9]EPO for users of providers who achieve certain annual objectives, as well as treatment with Sevelamer Carbonate in those patients with low blood phosphorus concentration (FNR, 2020).

[10]Most but not all private health insurances are part of FONASA. Some more expensive insurances are solely funded by premiums. One facility in the sample is owned by one such insurance, *Hospital Británico*.

Figure 2: Number of patients over time

Figure 3: Facilities' patients and capacity

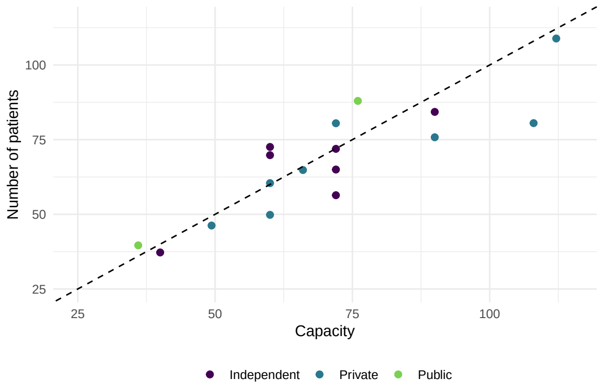


Figure 4: Facility choice

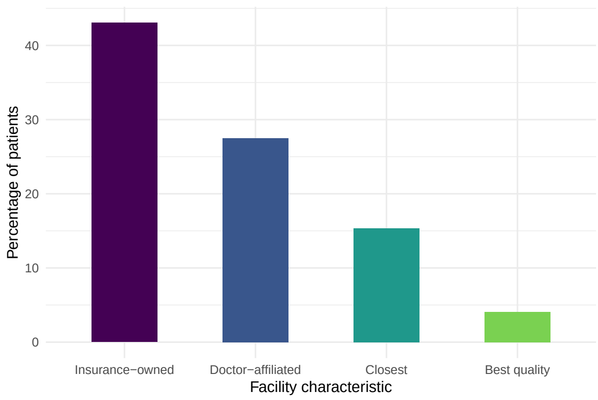
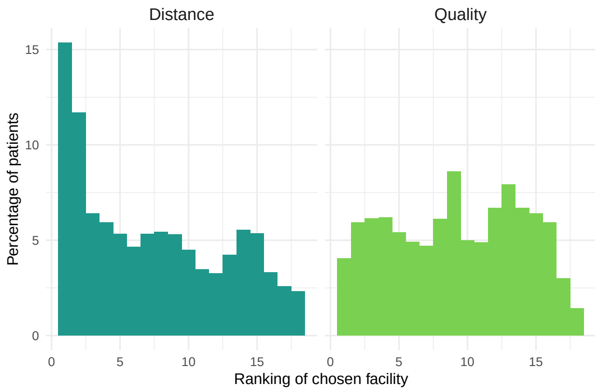


Figure 5: Ranking of chosen facilities



Note: Patients receiving dialysis 2004-2016 in Montevideo. Figure 2 plots average total number of patients in different facility types. Figure 3 shows the average yearly capacity and total patients in all facilities. Capacity is computed as the number of stations by number of shifts and is mostly fixed across time. Figure 4 plots the percentage of patients choosing facilities of different characteristics. "Insurance-owned" shows patients choosing a facility owned by their insurance, "Doctor-affiliated" shows patients choosing a facility where their Nephrologist works. "Closest" shows patients choosing the facility closest to their home. "Best quality" shows patients choosing the highest quality facility according to URR adequacy. Figure 5 plots the percentage of patients choosing facilities in each place in the ranking according to distance and quality (URR adequacy). "Private" represents facilities owned by private insurance companies. "Independent" represents private facilities non-associated with insurance companies. "Public" represents public facilities.

Public facilities are state-owned and managed. Two public hospitals have IMAEs who provide dialysis funded by the FNR (*Hospital de Clínicas* and *Hospital Maciel*). Public facilities tend not to pay for medications used during treatment and their payroll contributions are also subsidized by the government.

Independent facilities are owned by private firms solely in the dialysis market. They are for-profit firms whose only activity is dialysis provision. Most of them were founded by groups of nephrologists in the 1980s and were progressively bought by bigger firms starting in the late 1990's. Nowadays, Diaverum owns nine dialysis facilities (mostly outside the Capital city) and Ceneu owns seven facilities (mostly in the Capital city). Diaverum is a Swedish multinational ranked as the third biggest global dialysis clinic operator after

Table 1: Facilities' shares 2003-2016

Facility	Type	Patients	Percentage
Casmu	Private	418	12.96
Médica Uruguaya	Private	274	8.49
Uruguayana*	Independent	235	7.28
Asociación Española	Private	230	7.13
Casa de Galicia	Private	225	6.97
Hospital Maciel	Public	201	6.23
Hospital Evangélico	Private	180	5.58
SMI	Private	179	5.55
Intir**	Independent	174	5.39
Sedic*	Independent	167	5.18
Nephros	Independent	165	5.11
INU*	Independent	157	4.87
Renis**	Independent	155	4.80
Hospital Británico	Private	139	4.31
Sari	Independent	108	3.35
Hospital de Clínicas	Public	86	2.67
Universal	Private	70	2.17
Cedisa*	Independent	63	1.95
Total		3226	100.00

Note: Shares represent patient's choice at entry for patients entering dialysis 2003-2016 in Montevideo. *Facilities owned by Ceneu. **Facilities owned by Diaverum. There is no entry throughout the period; *Sari* is the only facility to exit in 2013. "Private" represents facilities owned by private insurance companies. "Independent" represents private facilities non-associated with insurance companies. "Public" represents public facilities. See Table 1 for a full list of facilities and shares.

Fresenius Medical Care and DaVita Inc (Schuetze, 2020). Ceneu is a national firm named Uruguayan Nephrologic Center, but previously associated with Fresenius. Facilites in Montevideo owned by each firm are listed in Table 1.

Between 2004 and 2017, the number of patients on chronic dialysis treatment has increased by 16%. In Figure 2 I plot the evolution of the average number of patients for different types of facilities. The growth in the number of patients is more notable in private and public facilities. In Figure 3 I plot the average yearly number of patients and capacity for each facility in the period. Facilities tend to be full or near full, and there is great variation in the capacity and number of patients across facilities. The capacity of facilities is mostly fixed throughout the period.

In the same period, the number of facilities has decreased by 8% (González-Bedat et al., 2020), which is likely the result of consolidation in the hemodialysis, peritoneal dialysis and pediatric dialysis markets. I document acquisitions and management agreements from 2001 to date in Table A1.

Dialysis facilities must be authorized by the MSP and comply with standards established by the FNR (FNR, 2020; Gambogi et al., 2020). All facilities must be able to operate at least three shifts a day and ensure the possibility of administering treatments outside of normal hours in case of emergencies (FNR, 2020). Interviews with industry professionals reveal there is screening but enforcement is soft. Additionally, entry is highly regulated if not prohibited, and negotiated with incumbent firms. No firms entered the market during my sample period, while only *Sari* exited the market in 2013 due to low patient load while achieving low treatment quality.

The FNR also sets quality targets and annually publishes facilities' performance on its website (fnr.gub.uy). These targets are not mandatory, which explains why many facilities don't achieve adequate thresholds[11]. Performance reviews are public but not salient, as they are in a unfriendly format, hard to access and highly complex for a typical advanced age patient. I show an example of such quality disclosure in Figure A7. In interviews, industry professionals are skeptic that patients are able to observe quality accurately.

In addition, successive MSP decrees regulate aspects of the physical plant, human resources and processes that each facility must carry out. In particular, ministerial ordinances regulate the number of professionals per shift and the number of patients that the facility must have. For example, ordinance No. 459 (2018) establishes that there must be at least one nephrologist per shift every 16 patients, and one nurse per shift for every 16 adult patients or 8 pediatric patients.

Patients can opt for a facility of their choice, which will be assigned as long as there is availability. This decision can be modified at any time with no need to express justification (FNR, 2020), although second choices are highly influenced by FNR administrative staff and motived by patient residence change. Only 10.7% of patients change facility after their first choice, and 97.4% of patients spend most of their treatment at their first-choice facility (Table 2). Capacity constraints are common, so patients may be rejected from a facility if it is full.

Multiple drivers of patient choice arise from interviewing doctors, managers and patients. The fact that a facility is owned by the patient's insurance makes it more likely that a patient chooses the facility, even though patients can choose any facility of their liking. This can be a rational decision, as attending a facility owned by one's insurance makes it easier to access medications, specialists and studies. The fact that the patient's nephrologist works at a certain facility makes it more likely that the patient chooses that facility. The distance between the patient's home and the facility is expected to negatively impact the probability of choosing the facility. This is highly related to the low mobility and low socioeconomic status of this population; patients often rely on their family or public

[11] Quality according to URR is highly heterogeneous accross facilities (Figure A3) but has been improving over time (Figure A4).

Table 2: Patient switching

Indicator	Mean	SD
Facilities attended per patient (#)	1.27	0.64
Patients changing facility (%)	10.70	
Patients spending most months at first facility (%)	88.87	
Months at first facility (%)	82.96	33.56
Months at most attended facility (%)	97.37	9.33

Note: Patients receiving dialysis 2004-2016 in Montevideo. "#" denotes count, "%" denotes percentage. For all measures I use the number of facilities a patient has been a member of, which does not include transitory treatment at a facility.

transport to get to their facility. At the same time, most facilities provide some kind of transportation for patients in need.

In Figure 4 I show the percentage of patients who choose a facility with these characteristics when they first enter dialysis. Patients who choose a facility owned by their insurance are around 43% of those those entering dialysis between 2003 and 2017 in Montevideo. Around 28% of patients choose a facility where their nephrologist has worked in that year. More than 15% of patients choose the facility that is nearest to their home. However, only 4% of patients choose the best quality facility according to their URR adequacy.

In Figure 5 I further examine the role of distance and quality. I plot the percentage of patients choosing each place in the ranking of facilities according to distance and quality. Patients tend to choose facilities higher in the ranking according to distance, while they don't seem to prefer facilities higher in the ranking according to quality. Almost 17% of patients choose a facility in the top 3 closer to their home.

The choice of facilities with these characteristics varies widely among patients attending different facility types. While almost all of patients attending public facilities also have public insurance, more than 60% of patients in private facilities are affiliated to the insurance that owns the facility, and almost none of the patients attending independent facilities have an insurance associated with that facility[12] (Figure A5).

In **Appendix B**, I explore the role of these drivers, especially distance and quality, for different types of patients.

[12] Although I define independent facilities as those that are not owned by an insurance, I assign Nephros as an independent facility owned by private insurance COSEM because of an agreement between these parties.

2.3 Effect of quality on survival

The validity of URR as a quality measure has been documented in the medical literature, as discussed in earlier sections. Nevertheless, I verify the relevance of this metric specifically within the patient population analyzed in this study. I empirically investigate the association between URR adequacy and patient survival in my sample to further justify its significance as a quality indicator.

To this end, I estimate the following regression model:

$$survival_{it} = \rho_0 + \rho_1 quality_{it} + P_i' \rho + \rho_2 insurance_i + \rho_3 month_t + \epsilon_{it}$$

In this equation, $survival_{it}$ is an indicator of survival for patient i in month t, while $quality_{it}$ indicates whether the patient's treatment meets the threshold for URR adequacy (0.65) in that same month. The vector P_i contains patient-level characteristics such as age and diabetes status. Additionally, the specification includes fixed effects for insurance type ($insurance_i$) and for the duration of treatment in months ($month_t$). I cluster standard errors at the patient level to account for within-patient correlation over time and restrict the sample to patients who have already died, thereby excluding those individuals whose survival outcomes extend beyond the observation window.

Table 3 presents the results of the regressions sequentially adding the listed controls, detailing the estimated effect of quality on patient survival across various specifications. Under my preferred specification, including all control variables and months-in-treatment as well as insurance type fixed effect, having an adequate level of URR in the treatment increases chances of survival by 0.5 pp or 0.51%.

Building upon these regression results, I then quantify the effect of treatment quality on life expectancy. To calculate the expected duration in treatment T, I employ the formula for the expected value of a geometric distribution given a monthly survival probability σ:

$$E(T) = \sum_{k=1}^{\infty} k\, \sigma^{k-1}(1-\sigma),$$

where k indicates the number of months. By factoring and solving this infinite series, the expected duration simplifies to:

$$E(T) = \frac{1}{1-\sigma}.$$

In the analyzed sample, the baseline monthly survival probability (σ) is estimated at 0.973. Given that achieving adequate URR improves the monthly survival probability by 0.005, I calculate the corresponding increase in expected treatment duration when receiving adequate treatment during all months. Under baseline conditions, the expected duration in

Table 3: Effect of quality on survival

	Survival (1)	Survival (2)	Survival (3)	Survival (4)
Quality	0.005*	0.003	0.005**	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Age	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Monthly sessions	0.028***	0.025***	0.026***	0.026***
	(0.001)	(0.001)	(0.002)	(0.002)
Decompensated start	-0.003	-0.003+	-0.004*	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
Female	-0.001	-0.001	-0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Diabetic		-0.002	-0.004+	-0.004*
		(0.002)	(0.002)	(0.002)
Cardiopathy		-0.006**	-0.006**	-0.006**
		(0.002)	(0.002)	(0.002)
Vascular peripheral disease		-0.005**	-0.004*	-0.004*
		(0.002)	(0.002)	(0.002)
Working		0.010***	0.008*	0.008**
		(0.003)	(0.003)	(0.003)
Smoking		-0.004	-0.005	-0.005
		(0.003)	(0.003)	(0.003)
Months in treatment FE			X	X
Insurance type FE				X
Observations	30,026	28,452	28,452	28,452
R^2	0.145	0.133	0.148	0.149

Note: Standard Errors clustered at the patient level (in parentheses). “Quality” is a dummy indicating the treatment reached the threshold for URR (0.65). “Decompensated start” is a dummy indicated the patient was decompensated at the start of the treatment. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

treatment is 37.2 months. When URR adequacy is reached, the monthly survival probability increases to 0.978, resulting in an expected duration of 45.7 months. Consequently, the attainment of adequate URR month after month translates into an increase in life expectancy of approximately 8.5 months, representing a substantial improvement of 22.9% relative to the baseline scenario.

3 Literature review

In recent years, important progress has been made in understanding the industrial organization of the dialysis market in the United States. Several features of this market are relevant to this paper.

Facilities face a trade-off between the quality of the service they provide and the number of patients they treat; for example, a facility can treat more patients if it spends less time cleaning dialysis stations, which increases infection rates (Grieco and McDevitt, 2017). At the same time, the more capacity a facility has, the less probability of entry there is in that market; however, facilities tend to enter the market with a given capacity and not change it post-entry (Dai and Tang, 2015). In fact, capacity remained constant for more than 90% of dialysis facilities in the US between 2004 and 2007 (Grieco and McDevitt, 2017).

This is an important aspect of this market because the effect of policy changes can vary substantially when taking into account entry and capacity investment; when these aspects are muted, geographic differentiation and congestion (number of patients conditioned on dialysis stations) greatly hinder quality competition (Eliason, 2022). Transportation costs play an important role even when entry and investment are held fixed; congestion is also relevant because patients may try to avoid facilities that are too crowded or may be rejected from facilities that are full (Eliason, 2022).

The fact that facilities may reject patients when they are full is an important challenge to demand estimation, as the choice set is then restricted in a manner not observed by the econometrician. This is accounted for in a methodology developed by Agarwal and Somaini (2022) and applied to the context of dialysis. They show that ignoring these supply-side constraints can lead to significant bias in estimates. Eliason (2022) overcomes this challenge by including the congestion of facilities into the utility function of patients, and instrumenting for congestion. However, this does not allow for separating the distate of patients for a crowded facility from the possibility that a facility is capacity-constraint.

In the last few years, the US dialysis market has undergone significant vertical and horizontal consolidation (Xia et al., 2024). This has been deemed a convenient setting to study the effect of mergers and acquisitions on quality supply. Acquisitions in the American dialysis market has a detrimental effect on patient outcomes for hospitalizations and mortality; however, this effects stems from a for-profit managerial strategy that uses less skilled human capital to increase profits, rather than market power (Eliason et al., 2020). A similar earlier finding in the medical literature linked for-profit ownership of dialysis facilities to increased mortality and decreased rates of placement on the waiting list for a renal transplant (Garg et al., 1999). Additionally, acquisitions lower quality as a result of facilities avoiding to steal patients from other facilities from the same firm; as a result, hospitalization rates rise while survival rates fall (Wollmann, 2020).

Other aspects of strategic behavior by dialysis facilities have been documented, some of them calling for better regulation of this market in the US. The use of a outcome-based payment (or pay-for-performance) scheme in the dialysis industry was gamed by facilities, strategically discharging patients who had worse outcomes to increase revenue;

while facilities can also increase revenue by increasing the quality of care, this is costly and reduces quantity supply (Bertuzzi et al., 2023). Relatedly, the use of epoetin alpha (EPO), a drug commonly prescribed to treat anemia among dialysis patients, has been shown to be highly sensitive to financial incentives and depend critically on the structure of the payment (reimbursement) scheme (Gaynor et al., 2023; Eliason et al., 2024).

More broadly, the effects of economic incentives on the quality of health care supply have been studied in non-dialysis settings related to this one. In the long-term care hospitals in the US, Einav et al. (2018) study the effect of a payment system that rewards hospitals up to a certain number of days of patient stay. They find large behavioral responses to this cutoff, but no effect on patient outcomes. In the nursing home market, where facilities compete on quality, Hackmann (2019) finds increasing the reimbursement rate would effectively increase the quality of care provided, measured as the number of skilled nurses per resident; however, a pro-competitive policy (public entry) does not increase quality. Similarly, in the context of Uruguayan health care provision, Fleitas (2020) finds a pro-competitive policy (reduced consumer lock-in) did little to increase the quality of health care, measured as relative hours worked by high-skill compared to low-skill specialists.

Evidence of information frictions has been documented in different health care markets. In the context of insurance choice, Handel et al. (2024) find that those better-off and more educated make meaningfully better health insurance choices in the Netherlands, and Handel et al. (2024) shows less-informed patients are willing to pay substantially more for the same insurance plan in the US. Similarly, Vatter (2022) finds information frictions reduce consumer surplus by approximately three monthly premiums in Medicare Advantage. In the context of provider choice, Cheng (2023) studies the demand for quality in the nursing home market, a setting where choice set restrictions are common. Employing the methodology developed by Agarwal and Somaini (2022), he finds residents are willing to tolerate a 28.6 percentage point higher probability of death in exchange for a one-mile reduction in travel distance. His evidence points to information frictions as responsible for the low quality demand, as older, cognitively impaired and less educated residents are less responsive to quality differences.

4 Theoretical framework

4.1 Supply

I follow Eliason (2022) in assuming facilities compete Bertrand-Nash in quality. This is an adaptation of the Bertrand-Nash competition on price. In our setting, price is set by the regulator, but quality is controlled by facilities.

Facility j chooses quality Qua_{jt} maximizing benefits of firm f, which owns facilities $r \in J_f$:

$$max_{Qua_{jt}} \sum_{r \in J_f} (p_t - mc_{rt}(Qua_{rt})) \cdot s_{rt}$$

where p_t is the price level (or reimbursement). mc_{rt} is the marginal cost of a dialysis treatment. s_{rt} is the share of patients attending facility r, for which I provide and expression below. Facilities then choose quality according to the following first order conditions:

$$\sum_{r \in J_f} \left[(p_t - mc_{rt}) \frac{\delta s_{rt}}{\delta Qua_{jt}} - \frac{\delta mc_{rt}}{\delta Qua_{jt}} s_{rt} \right] = 0$$

Here, facilities equalize the marginal cost of quality to the marginal revenue of quality. The revenue for each treatment or markup $(p_t - mc_{rt})$ is multiplied by the additional share of patients yielded by a marginal increase in quality $(\frac{\delta s_{rt}}{\delta Qua_{jt}})$. An increase in quality implies added costs for each treatment, which is measured by $\frac{\delta mc_{rt}}{\delta Qua_{jt}}$. This is then multiplied by the share of patients, to compute the marginal cost of an increase in the level of quality. I follow Eliason (2022) in assuming $\frac{\delta mc_{rt}}{\delta Qua_{jt}} = 0$ when $r \neq j$. That is: the quality level of a facility only impacts its own marginal cost.

In this kind of model, the regulator can propose different schemes that determine the price p paid to facilities for each treatment performed. Under a uniform price scheme p_u, the price is fixed at a certain amount:

$$p_u = \bar{p}$$

Introducing prices based on quality would modify the incentives that facilities face. In particular, the amount $\bar{p}$ would be multiplied by a term that depends on the relationship between the quality Qua_{jt} achieved by the facility j and a threshold $\bar{Qua}$ set by the regulator. In this way, the price based on quality p_{Qua} would have the following form:

$$p_{Qua} = (1 + \tau f(Qua_{jt}, \bar{Qua}))\bar{p}$$

Here, τ represents the reward or punishment established for achieving or not achieving a given quality level $\bar{Qua}$ (Camarda and Fleitas, 2022).

This framework is helpful in highlighting the importance of the demand for quality as an incentive for providing quality in this setting. Given that prices are set uniformly, and assuming the absence of non-profit motives, facilities will only provide quality treatments if that increases their revenues (via more patients) more than it increases their costs.

4.2 Demand

Following Eliason (2022), I model patient's choice as a discrete choice problem. Patient i chooses the facility that maximizes her expected utility among the available facilities.

I define the indirect utility U_{ijt} that patient i derives from facility j as follows:

$$U_{ijt} = \underbrace{\alpha_1 Ins_{ijt} + \alpha_2 Nep_{ijt} + \alpha_3 Dis_{ijt} + \alpha_4 Qua_{jt} + \beta' X_{jt} + \xi_{jt}}_{V_{ijt}} + \epsilon_{ij}$$

Ins_{ijt} is a binary variable indicating whether patient i is affiliated with an insurance that owns facility j. The variable Nep_{ijt} is a binary indicator of whether patient i is treated by a nephrologist that works at facility j. The term Dis_{ijt} denotes the distance from patient i's residence to facility j. Qua_{jt} captures the clinical quality of facility j and X_{jt} is a vector of other non-quality characteristics of facilities.

The term ξ_{jt} captures utility from facility j's unobserved attributes that is common across patients. Assuming the error term ϵ_{ij} is independently and identically distributed *Type 1 Extreme Value* (T1EV), the market share of each facility can be expressed as a function of V_{ijt} (McFadden, 1974; Berry, 1994):

$$s_{jt} = \sum_i \frac{\exp(V_{ijt})}{\sum_{j' \in J_i} \exp(V_{ij't})}$$

where J_i represents the set of facilities available for patient i. The choice set J_i is not exactly observable to the econometrician, as it is not uncommon that facilities reach full capacity and have to turn away patients. In the estimation section I implement an empirical strategy to account for this.

Although I describe this as the patient's decision, the model is agnostic as to whom is actually doing the deciding. Although some patients are perfectly able to make this type of decision at the moment of entering chronic dialysis, other patients who reach this point in poor health or old age may turn to familiy members or trusted doctors to make the decision for them.

Given that patients do not usually change facilities (Table 2), I only model their first choice. This implies assuming patients are not choosing to stay in the facility once they have entered dialysis and are in treatment.

Elasticities and semielasticities are relevant measures of demand for different characteristics. This demand structure yields the following probability of patient i choosing facility

j:

$$Pr_{ijt} = Pr(J_i = j) = \frac{\exp(V_{ijt})}{\sum_{k=1}^{J} \exp(V_{ik})}$$

Individual probabilities are then averaged to express the predicted market share of facility j:

$$s_{jt} = \sum_{i}^{N} Pr_{ijt}/N$$

For a continuous variable (e.g. Dis_{ijt}), we can compute elasticities (Train, 2009):

$$\begin{aligned} E_{ijt}^{D} = \frac{\delta Pr_{ijt}}{\delta Dis_{ijt}} \frac{Dis_{ijt}}{Pr_{ijt}} &= \alpha_3(1 - Pr_{ijt}) Pr_{ijt} \frac{Dis_{ijt}}{Pr_{ijt}} \\ &= \alpha_3(1 - Pr_{ijt}) Dis_{ijt} \end{aligned}$$

For a categorical variable (e.g. Ins_{ijt}), elasticities are undefined. We can compute semi-elasticities:

$$\begin{aligned} SE_{ijt}^{I} = \frac{(Pr_{ijt}^{1} - Pr_{ijt}^{0})/Pr_{ijt}^{0}}{Ins_{ijt}^{1} - Ins_{ijt}^{0}} &= \frac{\left[Pr_{ijt}(Ins_{ijt} = 1) - Pr_{ijt}(Ins_{ijt} = 0)\right] / Pr_{ijt}(Ins_{ijt} = 0)}{1 - 0} \\ &= \frac{Pr_{ijt}(Ins_{ijt} = 1) - Pr_{ijt}(Ins_{ijt} = 0)}{Pr_{ijt}(Ins_{ijt} = 0)} \end{aligned}$$

where $Pr_{ijt}^{1} - Pr_{ijt}^{0}$ is defined as the marginal effect. The (semi-)elasticity of facility j is an average of individual (semi-)elasticities with respect to facility j:

$$E_{jt} = \frac{1}{N} \sum_{i}^{N} E_{ijt}, \qquad SE_{jt} = \frac{1}{N} \sum_{i}^{N} SE_{ijt}$$

5 Data

I use longitudinal data (provided by agreement with the FNR) of hemodialysis patients between 2004 and 2017. For each patient, demographic characteristics, home location, clinical history, and monthly check-ups are available. Likewise, there is information on the hemodialysis facilities, including an identification variable of doctors responsible for treatments.

As all hemodialysis treatments in Uruguay are financed through the FNR, this represents the universe of patients doing dialysis in Uruguay.

The home address of the patients is also available and information on the geographic location of the IMAE is collected. The observed home address is the last one registered

Table 4: Patient's characteristics by type of facility

	Independent	Private	Public
Age at start | Dead	67.88	70.71	64.88
Age at death	70.84	73.51	68.11
Months on dialysis | Dead	39.17	36.48	40.36
Monthly sessions	8.81	9.85	7.64
Female (%)	42.2	36.55	48.95
Secondary education (%)	33.83	46.68	24.35
Retired (%)	38.27	51.24	28.4
Public insurance (%)	45.35	9.89	89.66
Private insurance (%)	36.34	83.13	1.18
Diabetic (%)	37.2	37.55	34.26
Cardiopathy (%)	26.78	34.32	22.04
Smoking (%)	11.72	9.03	14.33
Decompensated start (%)	72.93	75.81	80.73

Note: Patients entering dialysis 2003-2017 in Montevideo. Age and months on dialysis is not observed for patients entering dialysis before 2003 (although still on treatment). Hence, they are not shown in this table. "%" denotes percentage, value of other rows are averages by type of facility. "Private" represents facilities owned by private insurance companies. "Independent" represents private facilities non-associated with insurance companies. "Public" represents public facilities. See Table 1 for a full list of facilities and shares.

by the patient and no changes are observed in the home address, since this variable was rewritten in the administrative records. Figure 1 shows the locations of facilities in Montevideo and the geographic distribution of their patients.

I calculate the geodesic distance from the patient's home to each facility through *Google Maps*' API. The geodesic distance is defined as the shortest distance between two points in a straight line. I restrict my analysis to Montevideo, the Capital city. I do this because the rest of the country has one facility per province, which restricts patient choice set to essentially one option.

The resulting dataset features 3226 hemodialysis patients distributed among 18 facilities. 2779 of these patients are affiliated to an insurance that owns a facility. 447 are affiliated to an insurance that does not own any facilities. As shown in Table 1, out of the 18 facilities, 10 are owned by an insurance and 2 are publicly owned (which I interpret as being owned by the public insurance). Table 4 shows descriptive information of patients by type of facility.

I create a variable that indicates whether the patient's nephrologist has worked at each facility in a given year, and a variable that indicates whether a facility is owned by an insurance in a given year. Finally, I collect information on the number of facilities' shifts and stations by directly contacting industry executives and policymakers.

6 Empirical strategy

6.1 Quality scores

I quantify the quality of a facility based on patient-level treatment outcomes. However, patient outcomes are a function of both patient and provider inputs, and patients are not randomly distributed across providers. I separate quality inputs from the non-random sorting of patients by using risk-adjustment or value-added model, which accounts for sorting based on the observable attributes of patients (Einav et al., 2018; Eliason, 2022; Cheng, 2023).

The estimating equation is:

$$y_{ijt} = X_i\gamma + \mu_{jt} + \epsilon_{ijt}$$

where i indexes patients, j indexes provider, and t indexes month-years. The dependent variable, y_{ijt}, is a clinical outcome that is regressed on an array of time-invariant patient characteristics, X_i, and a provider-year constant, μ_{jt}.

Patient characteristics include risk factors like age, diabetes, cardiopathy, vascular peripheral disease and smoking (Table 4). Some patients start their treatment decompensated and this can influence their overall health, so this is important to take into account. It is also important to control for the number of months on dialysis because different patients are diagnosed with renal disease at different ages, and their condition tends to deteriorate with time. The number of monthly sessions is also included to control for the uptake of treatment, as some patients do not manage to attend the recommended amount of sessions. Other relevant characteristics are sex, working status and type of health insurance, which can control for other socioeconomic factors.

I interpret the provider-year constants as the average contribution of a provider to patient outcomes in a given year. This interpretation relies on the assumption that patient selection across dialysis providers is independent of any unobserved factors affecting patient outcomes, conditioning on the mentioned set of observables (Eliason, 2022). I recover each facility's risk-adjusted outcomes for the average patient ($\bar{X}_{ij}\hat{\gamma} + \hat{\mu}_{jt}$) and use them as quality scores at the facility-year level.

6.2 Demand

I estimate the model in two steps following Eliason (2022). This procedure mirrors Berry et al. (2004), without including random coefficients.

In a first step, I use Maximum Likelihood (ML) to estimate parameters related to patient-facility specific variables and employ a contraction mapping to estimate mean utilities. This model was estimated separately for two markets: patients whose insurance own a facility (*Has provider*), and those whose insurance does not own a facility (*No provider*). Both of this groups choose among the same set of facilities, but the former has the possibility to choose a facility owned by their own insurance. I consider all facilities in Montevideo as part of the choice set of all patients.

I estimate the following equation:

$$U_{ijt} = \alpha_1 Ins_{ijt} + \alpha_2 Nep_{ijt} + \alpha_3 Dis_{ijt} + \delta_{jt} + \epsilon_{ijt} \tag{1}$$

The mean utility term δ_{jt} captures the utility from facility j in year t that is assumed common across patients. The estimation of this parameter is a high computational burden in the Maximum Likelihood approach, as it involves estimating more than 200 parameters[13]. Hence, I employ a contraction mapping similar to Berry et al. (1995), commonly known as "BLP contraction":

$$\delta_{jt}^{k} = \delta_{jt}^{k-1}(\alpha) + log(s_{jt}^{obs}) - log(\hat{s}_{jt}(\delta_{jt}^{k-1}, \alpha))$$

where α is a vector containing $\{\alpha_1, \alpha_2, \alpha_3\}$. s_{jt}^{obs} is a vector of observed shares and $\hat{s}_{jt}(\delta_{jt}^{k-1}, \alpha)$ is a vector of predicted shares. This contraction mapping reaches a fixed point and I recover a vector of estimated $\hat{\delta}_{jt}$. In an outer loop, I estimate by maximum likelihood patient-specific parameters of variables Ins_{ijt}, Nep_{ijt} and Dis_{ijt}. For each iteration of this procedure an inner loop executes a BLP contraction that finds the value of δ_{jt} that matches observed shares for each facility-year.

In a second step, I use data at the facility-year level to decompose the mean utility into mean preferences for observed and unobserved attributes. I recover the fitted $\hat{\delta}_{jt}$ and project them onto facility-year attributes:

$$\delta_j = \alpha_4 Qua_{jt} + \alpha_5 Shi_{jt} + \alpha_6 Sta_{jt} + \alpha_7 Pat_{jt} + \xi_{jt} \tag{2}$$

where Shi_{jt} corresponds to the number of shifts in facility j in year t, Sta_{jt} accounts for the number of stations available (in each shift) and Pat_{jt} is the number of patients attending facility j in year t. Qua_{jt} are the quality scores constructed based on the risk-adjustment model.

The number of patients enters the mean utility both to account for patients' (dis)taste for a crowded facility and to control for possible choice set restrictions (i.e. the facility turning away patients due to being full) (Eliason, 2022). However, the number of patients in a

[13]In practice, an attempt to estimate this purely via Maximum Likelihood yields no convergence.

facility is obviously endogenous to desirable unobserved facility characteristics. Hence, I estimate equation 2 by Instrumental Variables (IV) instrumenting for Pat_{jt}.

I employ as instruments exogenous characteristics of competing facilities (i.e. "BLP instruments"). Demand for a facility is influenced by the characteristics of other facilities, hence providing exogenous variation in quantities (Berry and Haile, 2021). Specifically, I instrument the number of patients in facility j with the mean number of stations in all other facilities. The exclusion restriction is that facilities don't choose the number of stations with information of demand shocks. This is credible given that the number of stations is highly regulated, hence determined ex-ante by facilities.

6.3 Cost

With the demand estimates in hand, I now turn to the estimation of the marginal costs.

The first order conditions imply one equation per facility-year, and each of them have two unknowns: the marginal costs mc_{jt} and the effect of quality on marginal costs $\frac{\delta mc_{jt}}{\delta Qua_{jt}}$. Hence, I cannot solve first order conditions to back out the marginal cost directly as is common in the industrial organization literature[14].

I thus estimate a marginal cost function using generalized method of moments (GMM), following Eliason (2022). The moments are based on the first order conditions of facilities. To simplify estimation, I assume facilities maximize their own profits rather than the profits of the firm (single-product firms):

$$(p_t - mc_{jt})\frac{\delta s_{jt}}{\delta Qua_{jt}} - \frac{\delta mc_{jt}}{\delta Qua_{jt}} s_{jt} = 0$$

I parametrize the marginal cost function to depend on facility characteristics (including quality) and an additively separable error term v_{jt} which corresponds to unobserved marginal cost shocks. I assume the marginal cost function depends on treatment quality, facility type and chain affiliation:

$$\begin{aligned} mc_{jt} &= f(Qua_{jt}; \theta) + v_{jt} \\ mc_{jt} &= \theta_0 + \theta_1 Qua_{jt} + \theta_2 Independent_j + \theta_3 Public_j + \theta_4 Chain_j + v_{jt} \end{aligned}$$

[14] Crawford et al. (2019) back out both marginal costs and the effect of quality on marginal costs by solving first order conditions. However, in their setting, they can derive first order conditions for price as well as for quality. In the Uruguayan dialysis market the patients do not face prices at all.

Substituting this expression into the first order conditions:

$$(p_t - f(Qua_{jt};\theta) - v_{jt})\frac{\delta s_{jt}}{\delta Qua_{jt}} - \frac{\delta(f(Qua_{jt};\theta) + v_{jt})}{\delta Qua_{jt}} s_{jt} = 0$$

I then solve for v_{jt}:

$$v_{jt} = -\frac{\delta(f(Qua_{jt};\theta) + v_{jt})}{\delta Qua_{jt}} s_{jt} \left(\frac{\delta s_{jt}}{\delta Qua_{jt}}\right)^{-1} + p_t - f(Qua_{jt};\theta)$$

I assume providers know their unobserved cost shocks v_{jt} before choosing their quality. To address this endogeneity source, I employ demand-side instruments for quality: percentage of patients with diabetes and percentage of patients with heart disease at each facility-year. This allows me to formulate marginal cost moment conditions and sample analogs:

$$E(v_{jt} \times Z) = 0, \quad G(\theta) = \frac{1}{J}\sum_j v_{jt} Z$$

where Z is a vector of instruments. I use the two-step estimator from Hansen (1982) to estimate the marginal cost parameters.

7 Results

7.1 Quality scores

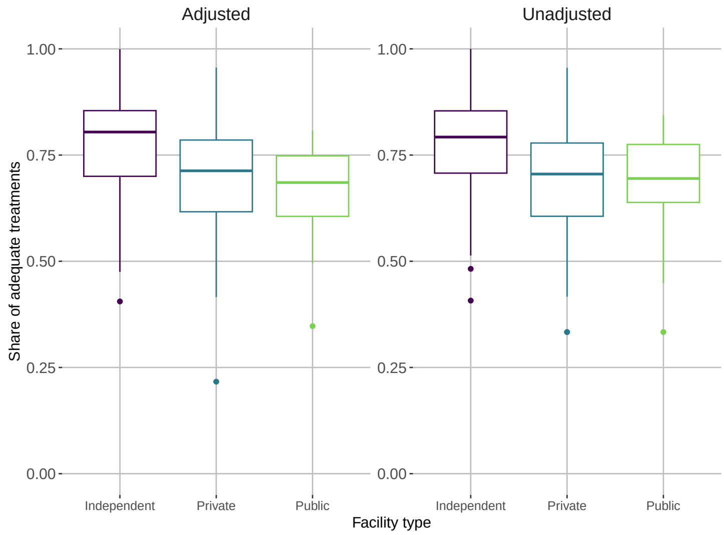
I estimate the presented model using adequate URR as the quality measure and use these quality scores as my definition of quality in demand estimation.

The dependent variable is thus a binary indicator of the treatment reaching the URR threshold of 0.65, which defines adequate treatments. I present the results in Table 5. Patients with diabetes and heart disease (cardiopathy or vascular peripheral disease) have on average worse results in terms of URR. Having diabetes reduces the probability of having an adequate treatment by 5.4 percentage points. Being female reduces this probability, on average, in 15.6 percentage points.

Table A2 shows quality measures (adequate URR and others) do not vary substantially in their mean or standard deviation with the risk-adjustment. This shows there is little influence from patients on quality outcomes.

I plot facility-year quality scores in Figure 6. There is substantial variation in the provision of quality according to URR: while some facilities provide adequate quality in 50% of treatments, others approach 100%. There is large overlap among independent, private and public facilities, although average levels tend to be higher for independent facilities.

Figure 6: Mean facility-year URR by facility type



Note: "Adjusted" shows risk-adjusted share of treatments that reach adequate URR levels, at the facility-year level. "Unadjusted" shows raw share of treatments that reach adequate URR levels, at the facility year-level. "Private" represents facilities owned by private insurance companies. "Independent" represents private facilities non-associated with insurance companies. "Public" represents public facilities. See Table 1 for a full list of facilities and shares.

The quality ranking of facilities (averaging over all years) varies little with adjustment, but there is some reordering (Figure A6).

7.2 Demand

Results yielded by the two-step demand estimation are compared to results from a Conditional Logit in Table 6[15]. At the same time, I show the results for both types of patients: those whose insurance owns a facility (*No provider*), and those whose insurance doesn't (*Has provider*). In this estimation, the "Quality" variable used are the quality scores constructed based on the risk-adjustment model.

All the patient-level estimates are very similar between the Conditional Logit and the two-step procedure. Insurance, Nephrologist and Distance are significant at the 0.1% level. Insurance and Nephrologist's estimated coefficients are positive, while Distance's coefficients are negative, across both types of patients and both estimation frameworks. Both in the Conditional Logit and in the two-step procedure, Nephrologist's coefficients in the *No provider* sample is much bigger than in the *Has provider* sample. This can be interpreted as patients choosing to "follow" their doctor more when they can't "follow"

[15]The two-step procedure iterates until convergence in the inner and the outer loop. The inner loop (contraction mapping) yields $max_j|log(s_{jt}^{obs}) - log(\hat{s}_{jt})| = 7.63 \times 10^{-6}$. At convergence, the outer loop (maximum likelihood) yields two succesive estimations of α_2 that are 6.21×10^{-6} apart.

Table 5: Risk-adjustment regression

	Quality
Age	0.001***
	(0.000)
Months on dialysis	0.001***
	(0.000)
Monthly sessions	0.003***
	(0.001)
Decompensated at start	-0.005
	(0.003)
Female	0.156***
	(0.003)
Diabetic	-0.054***
	(0.003)
Cardiopathy	-0.016***
	(0.004)
Vascular peripheral disease	-0.009*
	(0.004)
Working	-0.059***
	(0.004)
Smoking	-0.006
	(0.005)
Insurance type FE	X
Facility-year FE	X
Observations	77,576
Adjusted R^2	0.81

Note: "Quality" is a dummy indicating the treatment reached the threshold for URR (0.65). "Decompensated start" is a dummy indicated the patient was decompensated at the start of the treatment.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

their insurance.

Facility-level estimates are very different among the two estimation techniques. Importantly, the instrumented variable (Total patients) is positive for most patients (*Has provider*) in the Conditional Logit, but negative in the two-step procedure. This is likely due to the fact that in the Conditional Logit, the variable capturing the total number of patients is correlated with unobservable attributes that are valued by patients (and thus endogenous). However, in the two-step procedure, this variable is instrumented by a variable exogenous to unobservable attributes. Then, the coefficient becomes negative, as it likely captures the distaste of patients for attending a crowded facility or the restriction of the choice set due to the number of patients attending a facility (given the number of stations and shifts available, which I control for).

I present the first stage of the Instrumental Variable estimation in Table A3. As it is expected, the total number of patients at a given facility is affected negatively by the mean number of stations at other facilities. The Cragg-Donald and Kleibergen-Paap Wald statistics are non-robust and heteroskedasticity-robust analogues to the first-stage F statistics, respectively. However, in the case of one endogenous regressor, the Kleibergen-Paap Wald is equivalent to a non-homoskedasticity robust F-statistic (Andrews et al., 2019). The Cragg-Donald test yields values well beyond the critical value for a 10% maximum bias size, 16.38 (Stock and Yogo, 2005). The employed instruments are thus strong.

Turning to the estimated elasticities and semi-elasticities presented in Table 7, Quality presents the smaller absolute (semi)elasticity estimated. A 1% increase in the quality of a facility would increase patient load at that facility by 1.60%, on average. This is relatively little when compared to other drivers, like distance to facility and being affiliated to the insurance who owns the facility. A 1% decrease in the distance between a facility and a patient's home makes most patients (*Has provider*) 1.93% more likely to chose that facility. The fact that a patient's insurance owns a facility makes this patient 7.98 times more likely to chose this facility.

Either patients seem to be putting other elements above treatment quality when choosing facility, or there are information frictions that make it difficult for patients to assess a facility's treatment quality. The FNR publishes annual measures of facilities patient outcomes. Figure A7 shows an example of publicly available information about quality. The URR measure I use to construct quality scores is not directly observable for patients, but very correlated to Kt/V which is reported by the FNR. The correlation between URR and Kt/V is 0.75 at the facility-year level. However, from interviews with doctors and patients, this information does not seem to be actually used by patients when choosing a facility. Hence, it's reasonable to interpret these results as patients knowing little about

Table 6: Demand estimates

	Conditional Logit		Two-step procedure		
	Facility choice	Facility choice	Facility choice	Facility choice	Mean utility
	(1)	(2)	(3)	(4)	(5)
Patient level					
Insurance owns facility	2.250***		2.267***		
	(0.053)		(0.048)		
Nephrologist at facility	1.296***	2.225***	1.237***	2.257***	
	(0.072)	(0.140)	(0.066)	(0.132)	
Distance to facility	-0.355***	-0.411***	-0.367***	-0.317***	
	(0.014)	(0.041)	(0.014)	(0.033)	
Facility-year level					
Quality	0.590*	1.497**			2.296***
	(0.236)	(0.508)			(0.679)
Shifts	0.338***	0.389***			1.856***
	(0.052)	(0.105)			(0.147)
Stations	0.015	-0.189***			0.531***
	(0.009)	(0.041)			(0.073)
Total patients	0.012***	-0.012*			-0.116***
	(0.002)	(0.006)			(0.015)
Sample	Has provider	No provider	Has provider	No provider	All patients
Estimation method	ML	ML	ML	ML	IV
Observations	35,522	5,530	42,950	6,701	206

Note: Columns 1 and 2 show estimates from a Conditional Logit. Columns 3 to 5 show estimates from the two-step procedure outlined in subsection 6.2. The dependent variable in columns 1 to 4 is a dummy indicating facility choice of each patient. The dependent variable in column 5 is the facility-year level mean utility. "Quality" represents quality scores according to URR adequacy. Standard errors in parentheses. Sample: Conditional Logit and first step of two-step procedure estimated separately for patients whose insurance own a facility (*Has provider*), and those whose insurance does not own a facility (*No provider*). Estimation method: "ML" is Maximum Likelihood, "IV" is Instrumental Variable. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Elasticities and semi-elasticites

	Has provider	No provider	All patients
Patient level			
Insurance owns facility (SE)	7.98		
	(2.38)		
Nephrologist at facility (SE)	2.52	8.02	
	(0.55)	(2.42)	
Distance to facility (E)	-1.93	-1.69	
	(1.34)	(1.29)	
Facility-year level			
Quality (E)			1.60
			(0.36)
Shifts (E)			9.63
			(1.85)
Stations (E)			6.13
			(1.57)
Total patients (E)			-6.64
			(2.31)

Note: Elasticities and semi-elasticities are computed using estimates from the two-step procedure shown in Table 6. "(SE)" indicates estimates are semi-elasticities. "(E)" indicates estimates are elasticities. Estimates are means across patient groups (*Has provider*, *No provider* or *All patients*). Standard errors in parentheses.

the treatment quality they are receiving, and hence not choosing the facility that could provide them with the best quality.

To illustrate this point, I compute the Marginal Rate of Substitution (MRS) between distance and quality using my demand estimates.

$$\frac{\delta U/\delta x_l}{\delta U/\delta x_k} = MRS_{lk}$$

The marginal rate of substitution of good l for good k is the amount of good k that the consumer must be given to compensate her for a one-unit reduction in her consumption of good l, at current levels of goods l and k (Mas-Colell et al., 1995).

$$\frac{\delta U/\delta Dis}{\delta U/\delta Qua \times 0.01} = \frac{-0.367}{2.296 \times 0.01} = -15.984$$

Assuming full information, in exchange for a 1km decrease in the distance to their facility, a patient is willing to give up 15.9 percentage points in the probability of receiving an adequate treatment. This seems to be a MRS too large and implies it's not likely patients have full information in this market (Cheng, 2023).

The demand for the provider owned by the patient's insurance could also be interpreted as a way of seeking a better overall quality of health care. I gather from interviews that some doctors actually recommend this to patients seeking advise, as it makes treating complications, accessing prescriptions and receiving studies more easy and less time-consuming. When a patient attends a provider owned by their insurance, the doctors at this provider are usually also employed by the insurance. Thus, they can provide the needed paperwork for the patient to receive medication, treatment or diagnosis at their provider.

7.2.1 Non-equilibrium counterfactual

Geographic concentration is a salient characteristic of the Uruguayan dialysis market. This is a concern for patients and regulators, as health outcomes have been found to be negatively correlated to travel time to a dialysis facility in the Dialysis Outcomes and Practice Patterns Study (DOPPS) (Moist et al., 2008). Additionally, patients need to travel to the dialysis facility 3 times a week and patients further from facilities tend to come from less-well-off areas.

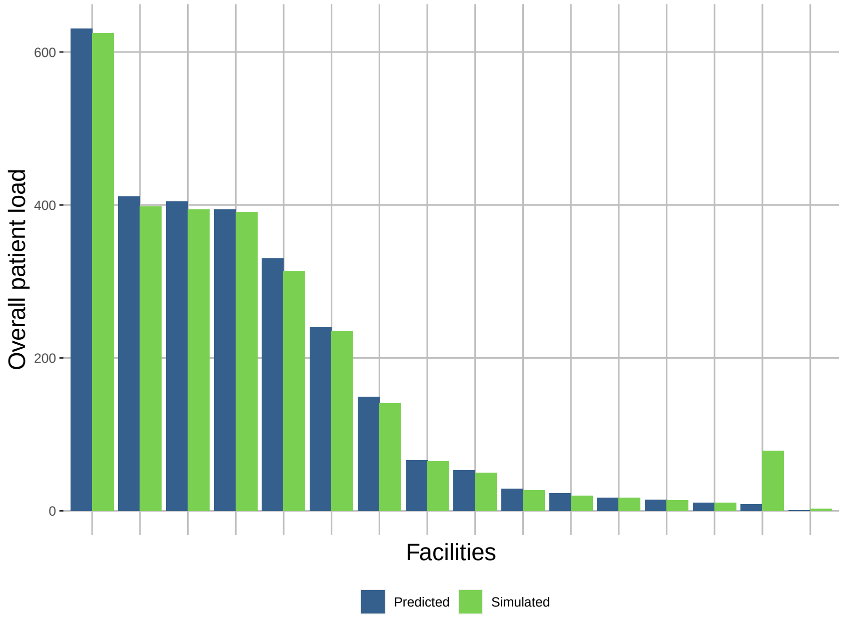
In this context, I simulate the move of a facility from the center of the city to the North-East, an underprovided area, which helps illustrate the relevance of distance in the preferences of patients. This facility is the third best in terms of provided quality[16].

To this end, I predict the choice of each of the patients that have entered dialysis in this period based on the demand estimates of the two-step procedure. A patient is assigned to the facility that gives her the most utility based on her characteristics and facility characteristics. I do this for patients in the *No provider* and the *Has provider* markets separately. I then simulate the move of the mentioned facility and recompute the distance to each of the patients' home addresses and predict the choice in this new situation. I hold other facility-level characteristics, as well as patient level characteristics, fixed. Facilities do not adjust quality once the facility moves location, and hence this is a non-equilibrium counterfactual.

In Figure 7, I show the patient count simulation with the facility move in comparison to the prediction of patient count based on current locations. The simulated move of the facility increases 7.8 times the patient load at that facility. In Figure A8, I show the predicted location of patients with the actual facility location ("Predicted") and the predicted location of patients with the counterfactual location ("Simulated"). Patients predicted to choose the facility in the counterfactual come overwhelmingly from the region near the facility.

[16]Specifically, I simulate a move from 8 de Octubre and Garibaldi to 8 de Octubre and Belloni, in Montevideo. One facility is removed from both the predicted and simulated sample, because it is no longer in the market (*Sari*).

Figure 7: Simulation of facility move



Note: "Simulated" shows predicted patient entry count based on the moved facility new location. "Predicted" shows predicted patient entry count based on current facility locations. Moved facility is second to last.

7.3 Cost

The marginal cost estimates are presented in Table 8. Across all specifications, quality makes up a sizable share of marginal costs. A 10 percentage point increase in the likelihood that a treatment achieves an adequate level of URR implies a cost of between 196.7 and 222.7 Uruguayan pesos per treatment, which is around 5% of the mean marginal cost. In other words, providing 100% treatments at an adequate level of URR would cost between 1967.7 and 2227.4 Uruguayan pesos per treatment, which is roughly double the mean estimated markup.

The mean percentage of adequate treatments in the facility-year sample is 73%. Providing this level of quality per treatment would cost 1626.1 pesos, which is 31.8% of the average marginal cost.

Facilities face high costs of providing quality which likely stem from inputs (like new filters and durable equipment) and specialized human capital (skilled nurses, technicians and nephrologists). This shows quality is costly, and thus facilities may have an incentive to underprovide quality to increase their margins.

The mean estimated markup remains stable across specifications at around 20% of the mean marginal cost. This is very close to what Eliason (2022) estimates for the dialysis market in the United States (18%)[17].

[17] For reference, De Loecker et al. (2020) estimate aggregate markups for the overall US economy were

The component of marginal cost that is unrelated to quality varies by facility type. As explained above, I classify facilities as public, private or independent. Public facilities are owned an managed by public hospitals, private facilities are owned and managed by private health insurance companies, and independent facilities are private firms but are not related to health insurance companies.

Independent facilities exhibit overall lower costs. As these facilities are not owned by a particular health insurance, dialysis is their only business and treatment is usually only source of revenue. This means they have for-profit status, unlike private facilites. The fact that they have a lower non-quality component of the marginal cost is consistent with a more efficient management of resources as well as a clearer profit motive. This may not result in an overall lower marginal cost, as these facilities seem to be some of the ones providing best quality treatment. It is possible these facilities are also more efficient at providing quality; however, this specification cannot speak to possible differences in the efficiency of quality provision.

On the other hand, public facilities have a higher non-quality component of marginal cost, which is consistent with the fact that they do not actually need to have a profitable operation. It's worth remembering that public facilities are subsidized in their human capital costs as well as some of their drug expenses; as far as public facilities' management do not internalize these costs when making decisions about quality provision, these costs are not included in my marginal costs estimation. Hence, this is likely a lower bound of the marginal costs of public facilities.

This estimation framework assumes marginal costs and the effect of quality on marginal costs do not change with the amount of treatments provided or patients[18].

In Table A4 I show a first stage of the instrumental variables employed. Wald tests indicates these instruments are relevant and strong.

20% in 1980 and have risen to 61% in 2019.

[18]In practice, an attempt to let the marginal cost vary with quantity yielded no convergence.

Table 8: Marginal cost estimates

	(1)	(2)	(3)	(4)
Constant	3650.8**	4115.7***	3829.3**	3513.2*
	(1345.8)	(1034.4)	(1180.6)	(1386.9)
Quality	2078.6	1751.7*	1967.7*	2227.4*
	(1062.6)	(835.5)	(943.7)	(1113.3)
Independent		-123.9	-118.6	-251.1
		(83.09)	(85.54)	(173.4)
Public			87.99	97.69
			(105.8)	(113.0)
Chain FE				X
Observations	210	210	210	210
Mean marginal cost	5,174.2	5,342.9	5,227.2	5,089.6
Mean markup	1,080.5	911.8	1,027.5	1,165.0

Note: Estimates of marginal cost function estimated by GMM. Variables are at the facility-year level. Quality is the average level proportion of URR adequacy. "Independent" represents private facilities non-associated with insurance companies. "Public" represents public facilities. "Private" (the omitted category) represents facilities owned by private insurance companies. Chain fixed effects absorb the effect of being owned by the three main independent facility chains. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

8 Equilibrium counterfactuals

8.1 Pay for performance

To introduce pay-for-performance (P4P) incentives into our economic model, I modify the fixed pricing mechanism by allowing prices to depend directly on quality outcomes. Specifically, the modified price, denoted as p_{Qua}, is derived by adjusting the baseline price p through a function of the difference between observed quality Qua and a pre-specified quality threshold $\bar{Qua}$. Formally, this relationship is represented as:

$$p_{Qua} = \left[1 + \tau(Qua - \bar{Qua})\right] \bar{p},$$

where τ measures the sensitivity of price adjustments to deviations from the quality threshold $\bar{Qua}$. Under this framework, each incremental improvement in quality above the threshold enhances the price providers receive, while each decrement below it results in a corresponding price reduction.

Facilities now face an optimization problem characterized by the objective of maximizing their profits through the choice of Qua_j, defined by[19]:

$$\max_{Qua_j} \ (p_{Qua} - mc_j(Qua_j)) \cdot s_j(Qua_j).$$

The resulting first-order conditions show how price sensitivity introduces an additional term:

$$(p_{Qua} - mc_j)\frac{\delta s_j}{\delta Qua_j} + \left(\frac{\delta p_{Qua}}{\delta Qua_j} - \frac{\delta mc_j}{\delta Qua_j}\right) s_j = 0.$$

This additional term $\frac{\delta p_{Qua}}{\delta Qua_j} s_j$ captures the financial impact of quality adjustments across all patients. Pay-for-performance reshapes incentives by linking financial rewards directly to realized quality.

Because patient utilities depend on the number of patients treated, reflecting congestion effects, market shares both determine utilities and are determined by them. Equilibrium computation therefore involves an iterative algorithm that toggles between calculation of utilities and shares until convergence, in the vein of Bayer and Timmins (2005).

In computing this model, I set the quality threshold at 0.8, implying that providers are rewarded (penalized) if more (less) than 80% of their patients receive adequate treatment in terms of URR. Thus, the model's policy implications are anchored in realistic expectations of quality supply, although marginal modifications to the threshold do not significantly alter results.

8.2 Goodness of fit

Facilities in the period actually face, on average a price of $\bar{p} = 6346$ (and $\tau = 0$). I compute this equilibrium to get a measure of goodness of fit. I then compare the overall share and mean quality at the facility level throughout the period. Equilibrium shares and quality follow predicted shares and quality (Figure 8 and Figure 9). This gives empirical support to the partial equilibrium framework and estimates, which I proceed to compute with counterfactual price schemes.

8.3 Counterfactual results

To assess the impact of varying the price-sensitivity parameter (τ) and the base price ($\bar{p}$), I compute equilibrium outcomes over a broad grid of $(\tau, \bar{p})$ combinations. From these simulations, I retain only those equilibria that yield perfect quality—defined as 100% of treatments classified as adequate under the URR metric.[20] For each equilibrium, I

[19] I assume single-product firms to make the counterfactual computation coherent with cost estimation.
[20] See Figure A9 for the full grid of outcomes, including those with less than perfect quality.

Figure 8: Predicted vs actual shares

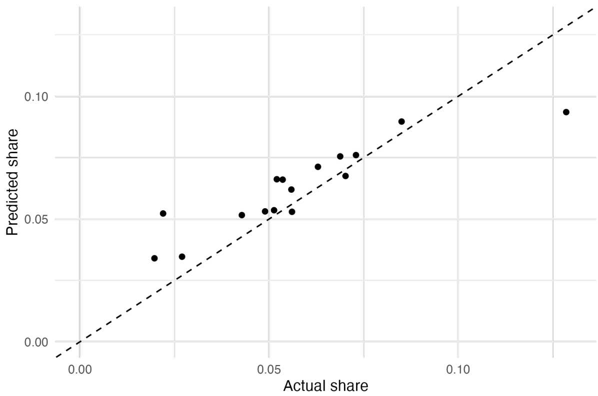
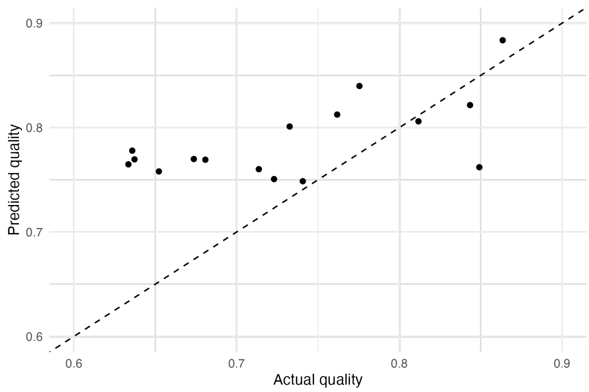


Figure 9: Predicted vs actual quality



Note: Plots are at the facility level. Actual shares are overall shares of new patients throughout the 2004-2017 period. Actual quality are mean average quality values throughout the 2004-2017 period. The quality measure used is the proportion of treatments with adequate URR level. Dashed line is 45 degree line.

compute total government spending and divide it by the number of treatments to obtain an *average paid price*, which represents the government's per-treatment expenditure.

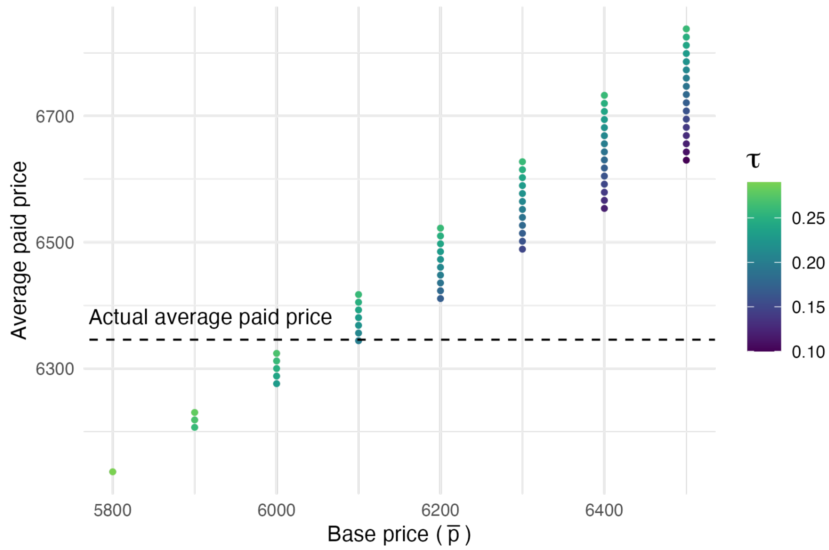
Figure 10 presents the results, plotting the average paid price (vertical axis) against the base price $\bar{p}$ (horizontal axis), with different values of τ denoted by color. The dashed horizontal line at \$6,346 indicates the average paid price under the status quo—corresponding to a fixed-price reimbursement scheme that achieves approximately 72.4% treatment adequacy.

Equilibrium outcomes below this line represent policy scenarios that simultaneously attain perfect quality and reduce the average price relative to the status quo. These results suggest that a pay-for-performance scheme could increase the share of adequate treatments by 27.6 percentage points (a 37.1% improvement) while lowering public expenditure. The mechanism underlying these gains is a reduction in providers' markups, with no changes in entry or patient allocation.

The equilibrium with the lowest spending among the high-quality scenarios occurs at $\tau = 0.29$ and $\bar{p} = 5800$. This configuration features a base price below the current fixed price and a relatively steep quality premium. It reduces the average government-paid price from \$6,345.65 to \$6,136.40—a 3.3% spending reduction—and lowers the average markup from 23.23% to 6.43%, reflecting a substantial shift in provider incentives toward quality provision. Given that government yearly spending on dialysis treatments was 90.5\$ million in 2017, the estimated savings amount to \$2.9 million.

I extend the analysis by examining three additional counterfactual policy scenarios, summarized in Table 9:

Figure 10: Pay-for-performance counterfactuals



Note: Each point represents an equilibrium outcome with perfect quality under different price parameters. Base price ($\bar{p}$) is the baseline level of the pay-for-performance payment scheme. Average price paid is the average price paid by the government per treatment. τ is the reward/penalty parameter for departing from the set quality threshold. Actual average price is the average price paid per treatment by the government averaged over the 2004-2017 period.

Mandated quality. In this scenario, the government imposes perfect quality as a regulatory standard and sets a uniform reimbursement price equal to the maximum marginal cost (\$5,819.12). This policy achieves full quality at the lowest average price among all scenarios, with the average markup falling to just 0.93% of the marginal cost.

High demand. Here, I double the demand parameter for quality (α_4), simulating a setting with higher patient awareness or reduced information frictions. Without changing the uniform price, this scenario induces providers to supply perfect quality, reducing average markups from 23.23% to 10.12% due to increased competitive pressure.

High demand + pay-for-performance: Combining enhanced patient demand with a P4P scheme results in an optimal equilibrium at $\tau = 0.18$ and $\bar{p} = 5900$, achieving perfect quality at an average paid price of \$6,112.40—lower than either component policy alone. Markups remain at 6.01%, similar to the standalone P4P scenario.

These scenarios collectively underscore that both regulatory and market-based interventions can realign provider incentives, improve quality, and reduce inefficiencies in dialysis provision. All approaches effectively reduce providers' market power, compressing provider markups and improving patient welfare, though they differ in informational and implementation requirements.

The *Mandated quality* policy yields the lowest markup by aligning reimbursement with the

Table 9: Equilibrium comparison

	Parameters			Results		
Equilibrium	$\bar{p}$	τ	α_4	Avg paid price	Avg quality	Avg markup
Actual	6345.65	0.00	2.30	6345.65	73.30%	23.23%
Pay-for-performance	5800.00	0.29	2.30	6136.40	100.00%	6.43%
Mandated quality	5819.12	0.00	2.30	5819.12	100.00%	0.93%
High demand	6345.65	0.00	4.59	6345.65	99.87%	10.12%
High demand + P4P	5900.00	0.18	4.59	6112.40	100.00%	6.01%

Note: Each row shows parameters and results for a different equilibrium. $\bar{p}$ is the base price (equal to the price when price is uniform), is the reward/penalty parameter for departing from the quality threshold of 0.8 (is 0 when price is uniform). α_4 is the demand for quality. "Avg paid price" is the average price paid by the government per treatment. "Avg quality" is the average level of quality, measured as the proportion of adequate treatments. "Avg markup" is the average markup as a percentage of marginal cost. "Actual" is statu quo (uniform price and low demand for quality). "Pay-for-performance" implements a price dependent on quality as described in subsection 8.1 (result shown corresponds to lowest average price paid with perfect quality). "Mandate quality" enforces obligatory perfect quality, while setting a uniforme price at the maximum marginal cost. "High demand" doubles demand for quality. "High demand + P4P" both doubles demand for quality and implements a price dependent on quality as described in subsection 8.1 (result shown corresponds to lowest average price paid with perfect quality).

highest marginal cost. However, it requires granular cost information at the facility level to set a price at the maximum marginal cost, posing practical implementation challenges.

By contrast, *Pay-for-performance* policies do not require detailed cost data. As shown in Figure 10, a wide range of $(\tau, \bar{p})$ combinations can achieve perfect quality with lower markups (6.43%). This flexibility makes these schemes particularly attractive, as they reduce informational burdens while still effectively incentivizing quality.

Finally, increasing patient demand for quality (*High demand*) independently curbs market power and induces quality improvements, highlighting the importance of addressing information frictions. Combining this demand-side pressure with P4P incentives (*High Demand + P4P*) yields further efficiency gains, suggesting strong complementarities between regulatory and market-driven approaches.

9 Conclusion

This study examines the demand for and supply of quality in the Uruguayan dialysis market. I estimate that the selected quality measure—adequate URR—increases life expectancy after diagnosis by 8.5 months (22.9%). Facility-specific quality scores show that providers play a key role in patient outcomes. Using these scores, I estimate a demand model for facility choice that accounts for unobserved congestion, and recover marginal costs using an IV strategy. I find that delivering average-quality care accounts for 31.8% of the marginal cost.

Demand for quality appears limited: patients are willing to accept a 15.9 percentage point drop in adequate treatment probability to reduce travel distance by 1 km, highlighting the role of non-quality factors in choice.

The observed variation in quality across facilities appears to stem from the uniform pricing scheme, limited patient responsiveness to quality (likely due to information frictions) and the high costs of quality improvements. In the absence of targeted incentives, providers underinvest in quality, prioritizing cost containment over patient outcomes. Public intervention through well-designed incentive mechanisms, such as pay-for-performance, emerges as an effective strategy to encourage quality improvements while maintaining or reducing costs.

Counterfactuals suggest that a pay-for-performance scheme could improve quality by 27 percentage points (36%) while reducing government spending by 3.3% (approximately $2.9 million). This also reduces markups from 23% to 6%. Mandated reimbursement at marginal cost achieves similar quality with lower markups but requires detailed cost data. Pay-for-performance achieves comparable outcomes with less informational burden. Higher demand for quality can also complement incentive-based policies, further reducing markups.

These results underscore the potential of performance-based incentives to improve quality and contain costs, even in the presence of low demand for quality and market power. By tying payments to observable outcomes, pay-for-performance offers a feasible alternative to more data-intensive regulatory approaches. The findings highlight the importance of policy design, suggesting that well-calibrated incentives can realign provider behavior when information frictions limit quality investment.

More broadly, these results contribute to the economic literature on healthcare incentives, demonstrating how financial mechanisms can enhance service quality and fiscal efficiency, particularly in dialysis markets in developing countries. Given the significant role of dialysis treatments in public health, their disproportionate impact on lower-income populations, and their fiscal burden, performance-based payment models offer a promising avenue for improving provider incentives, optimizing healthcare expenditures, and addressing health disparities.

References

Agarwal, N. and Somaini, P. J. (2022). Demand analysis under latent choice constraints. *National Bureau of Economic Research*.

Andrews, I., Stock, J. H., and Sun, L. (2019). Weak instruments in instrumental variables regression: Theory and practice. *Annual Review of Economics*, 11(1):727–753.

Bayer, P. and Timmins, C. (2005). On the equilibrium properties of locational sorting models. *Journal of Urban Economics*, 57(3):462–477.

Bello, A. K., Okpechi, I. G., Levin, A., Ye, F., Damster, S., Arruebo, S., Donner, J.-A., Caskey, F. J., Cho, Y., Davids, M. R., et al. (2024). An update on the global disparities in kidney disease burden and care across world countries and regions. *The Lancet Global Health*, 12(3):e382–e395.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, pages 242–262.

Berry, S. T. and Haile, P. A. (2021). Foundations of demand estimation. In *Handbook of industrial organization*, volume 4, pages 1–62. Elsevier.

Berry, S. T., Levinsohn, J. A., and Pakes, A. S. (1995). Automobile prices in market equilibrium. *Econometrica*, pages 841–890.

Berry, S. T., Levinsohn, J. A., and Pakes, A. S. (2004). Differentiated products demand systems from a combination of micro and macro data: The new car market. *Journal of Political Economy*, 112(1):68–105.

Bertuzzi, L., Eliason, P. J., Heebsh, B., League, R. J., McDevitt, R. C., and Roberts, J. W. (2023). Gaming and effort in performance pay. *National Bureau of Economic Research*.

Camarda, E. (2022). Welfare effects of outcome-based prices in the english national health service. *Working paper*.

Camarda, E. and Fleitas, S. (2022). Patient choice, payment systems and multidimensional quality. *Working paper*.

Cheng, A. (2023). Demand for quality in the presence of information frictions: Evidence from the nursing home market. *Working paper*.

Chesnaye, N. C., Ortiz, A., Zoccali, C., Stel, V. S., and Jager, K. J. (2024). The impact of population ageing on the burden of chronic kidney disease. *Nature Reviews Nephrology*, 20(9):569–585.

Crawford, G. S., Shcherbakov, O., and Shum, M. (2019). Quality overprovision in cable television markets. *American Economic Review*, 109(3):956–95.

Dai, M. and Tang, X. (2015). Regulation and capacity competition in health care: Evidence from us dialysis markets. *Review of Economics and Statistics*, 97(5):965–982.

De Loecker, J., Eeckhout, J., and Unger, G. (2020). The rise of market power and the macroeconomic implications. *The Quarterly Journal of Economics*, 135(2):561–644.

Dranove, D. and Satterthwaite, M. A. (1992). Monopolistic competition when price and quality are imperfectly observable. *The RAND Journal of Economics*, pages 518–534.

Einav, L., Finkelstein, A., and Mahoney, N. (2018). Provider incentives and healthcare costs: Evidence from long-term care hospitals. *Econometrica*, 86(6):2161–2219.

Eliason, P. J. (2022). Price regulation and market structure: Evidence from the dialysis industry. *Working paper*.

Eliason, P. J., Heebsh, B., League, R. J., McDevitt, R. C., and Roberts, J. W. (2024). Patient heterogeneity and treatment choices: Evidence from the dialysis industry. *Working Paper*.

Eliason, P. J., Heebsh, B., McDevitt, R. C., and Roberts, J. W. (2020). How acquisitions affect firm behavior and performance: Evidence from the dialysis industry. *The Quarterly Journal of Economics*, 135(1):221–267.

Fleitas, S. (2017). The costs of lock-in in health care markets: Evidence from hospital choice in Uruguay. *Working paper*.

Fleitas, S. (2020). Who benefits when inertia is reduced? Competition, quality and returns to skill in health care markets. *CEPR Discussion Paper*.

FNR (2020). Tratamiento Dialítico Crónico: Informe técnico.

Foundation, N. K. (2015). KDOQI clinical practice guideline for hemodialysis adequacy: 2015 update. *American Journal of Kidney Diseases*, 66(5):884–930.

Francis, A., Harhay, M. N., Ong, A., Tummalapalli, S. L., Ortiz, A., Fogo, A. B., Fliser, D., Roy-Chaudhury, P., Fontana, M., Nangaku, M., et al. (2024). Chronic kidney disease and the global public health agenda: an international consensus. *Nature Reviews Nephrology*, pages 1–13.

Gambogi, R., Fernández, G., Ausqui, C., Baldizzoni, M., Chifflet, L., Cichero, M., Álvaro Focone, Leiva, G., and Wald, I. (2020). *Estándares de evaluación y seguimiento*. Montevideo, 3rd edition.

Garg, P. P., Frick, K. D., Diener-West, M., and Powe, N. R. (1999). Effect of the ownership of dialysis facilities on patients' survival and referral for transplantation. *New England Journal of Medicine*, 341(22):1653–1660.

Gaynor, M., Mehta, N., and Richards-Shubik, S. (2023). Optimal contracting with altruistic agents: Medicare payments for dialysis drugs. *American Economic Review*, 113(6):1530–71.

González-Bedat, M. C., Ferreiro-Fuentes, A., and Ceretta, M. L. (2020). Registro Uruguayo de Diálisis: Informe anual 2018.

Grieco, P. L. and McDevitt, R. C. (2017). Productivity and quality in health care: Evidence from the dialysis industry. *The Review of Economic Studies*, 84(3):1071–1105.

Hackmann, M. B. (2019). Incentivizing better quality of care: The role of medicaid and competition in the nursing home industry. *American Economic Review*, 109(5):1684–1716.

Handel, B., Kolstad, J., Minten, T., and Spinnewijn, J. (2024). The socioeconomic distribution of choice quality: Evidence from health insurance in the netherlands. *American Economic Review: Insights*, 6(3):395–412.

Handel, B. R. and Kolstad, J. T. (2015). Health insurance for "humans": Information frictions, plan choice, and consumer welfare. *American Economic Review*, 105(8):2449–2500.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica: Journal of the econometric society*, pages 1029–1054.

Jamison, D. T. (2018). Disease control priorities: improving health and reducing poverty. *The Lancet*, 391(10125):e11–e14.

Lee, A., Gudex, C., Povlsen, J. V., Bonnevie, B., and Nielsen, C. P. (2008). Patients' views regarding choice of dialysis modality. *Nephrology Dialysis Transplantation*, 23(12):3953–3959.

Liyanage, T., Ninomiya, T., Jha, V., Neal, B., Patrice, H. M., Okpechi, I., Zhao, M.-h., Lv, J., Garg, A. X., Knight, J., et al. (2015). Worldwide access to treatment for end-stage kidney disease: a systematic review. *The Lancet*, 385(9981):1975–1982.

Mas-Colell, A., Whinston, M. D., and Green, J. R. (1995). *Microeconomic Theory*. Oxford University Press.

McFadden, D. (1974). The measurement of urban travel demand. *Journal of Public Economics*, 3(4):303–328.

Moist, L. M., Bragg-Gresham, J. L., Pisoni, R. L., Saran, R., Akiba, T., Jacobson, S. H., Fukuhara, S., Mapes, D. L., Rayner, H. C., Saito, A., et al. (2008). Travel time to dialysis as a predictor of health-related quality of life, adherence, and mortality: the dialysis outcomes and practice patterns study (dopps). *American Journal of Kidney Diseases*, 51(4):641–650.

Owen, W. F., Lew, N. L., Liu, Y., Lowrie, E. G., and Lazarus, J. M. (1993). The urea reduction ratio and serum albumin concentration as predictors of mortality in patients undergoing hemodialysis. *New England Journal of Medicine*, 329(14):1001–1006.

Schuetze, A. (2020). Swedish dialysis firm diaverum targets ipo in november (reuters). October 29, 2020, Accessed: 2024-09-20.

Stock, J. and Yogo, M. (2005). *Testing for Weak Instruments in Linear IV Regression*, pages 80–108. Cambridge University Press, New York.

Train, K. E. (2009). *Discrete choice methods with simulation.* Cambridge University Press.

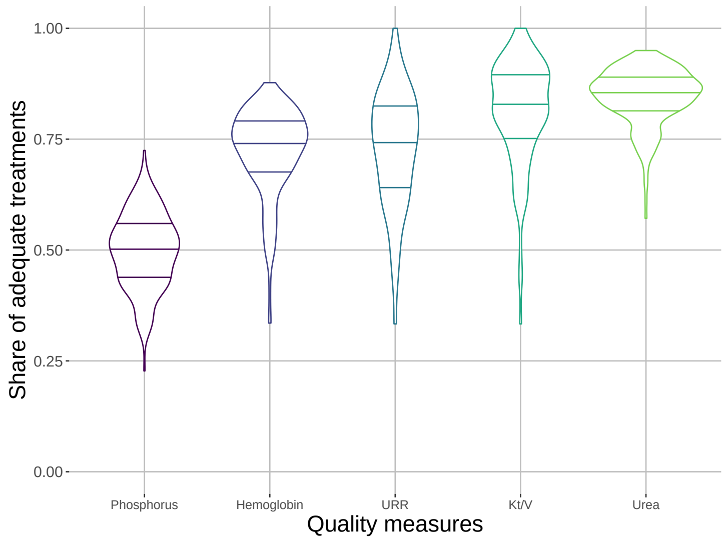
Vatter, B. (2022). Quality disclosure and regulation: Scoring design in medicare advantage. *Working paper.*

Wollmann, T. G. (2020). How to get away with merger: Stealth consolidation and its effects on us healthcare. *National Bureau of Economic Research.*

Xia, X., Deng, W., Eliason, P., League, R. J., McDevitt, R. C., Roberts, J. W., and Wong, H. (2024). Financial ties, market structure, commercial prices, and medical director compensation in the us dialysis industry: 2005 – 2019. *Working Paper.*

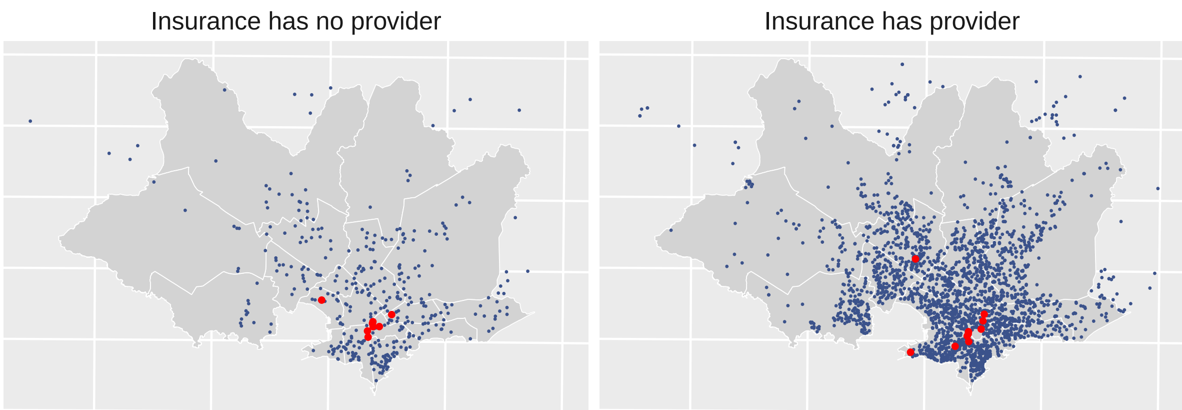
Appendix A: Additional figures and tables

Figure A1: Treatment quality across facility-years



Note: For each measure, I plot the share of treatments that achieve an adequate level according to Uruguayan regulator's quality standards or international standards: URR $>$ 0.65, Kt/V $>$ 1.2, Hemoglobin $>$ 10 g/dl, Urea $<$ 1,7 mg/l, Phosphorus $<$ 5,5 mg/l. Horizontal lines show 25th, 50th and 75th percentiles.

Figure A2: Patient and facility location by facility type



Note: Patients entering dialysis 2003-2017 in Montevideo. Red dots represent facilities location, blue dots represent patients' homes.

Figure A3: Average quality by facility

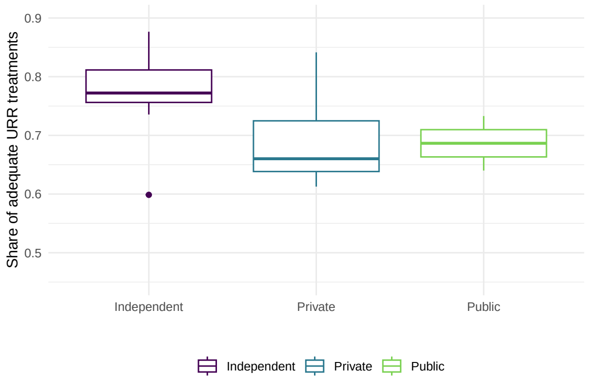
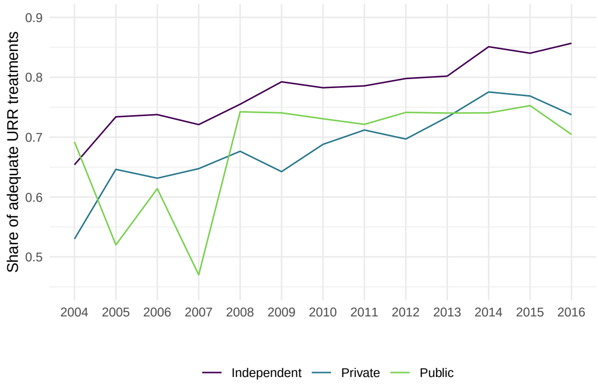
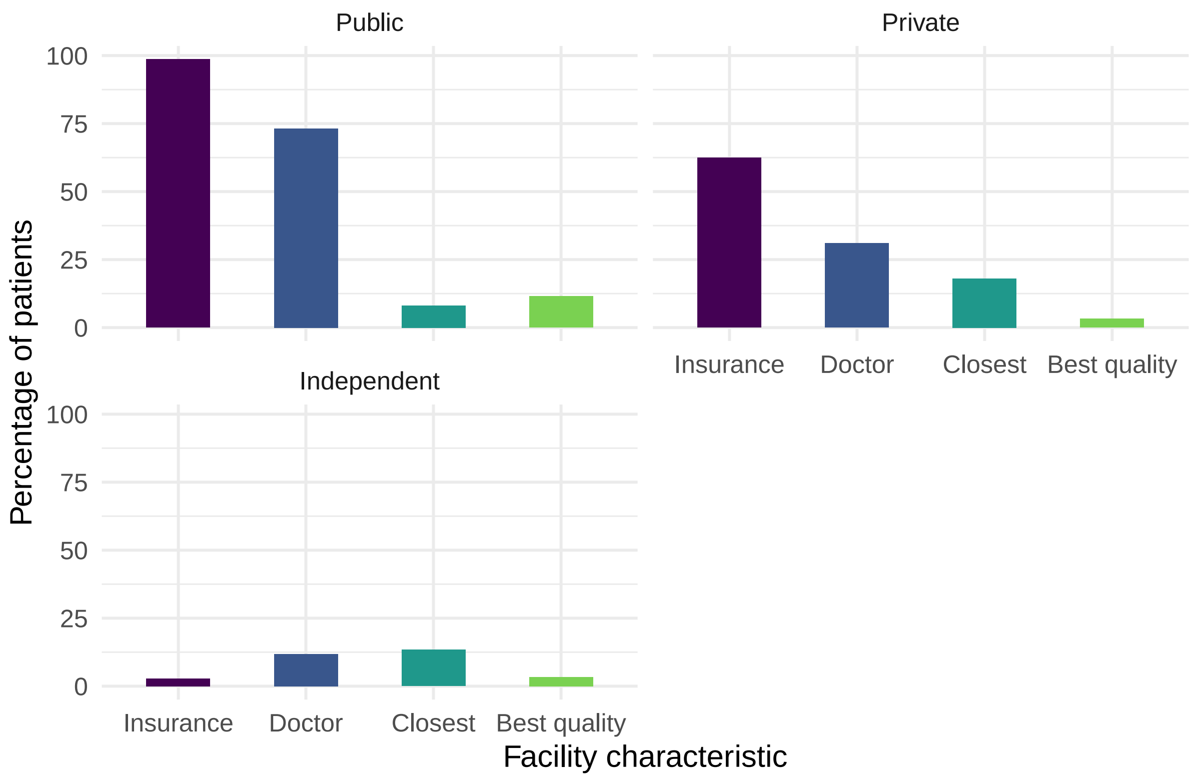


Figure A4: Average quality over time



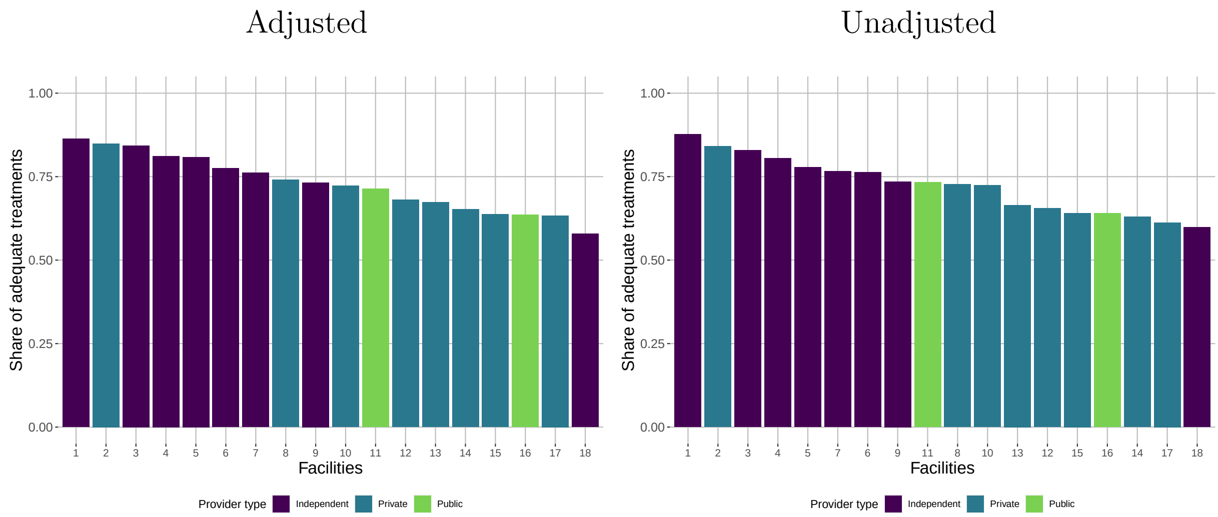
Note: Patients attending dialysis 2004-2017 in Montevideo. The first figure shows the variation in the average share of patients receiving adequate URR treatment across facilities. The second figure shows the evolution of the average yearly share of patients of patients receiving adequate URR treatment over time.

Figure A5: Facility choice by chosen facility type



Note: Patients entering dialysis 2003-2016 in Montevideo. The figure plots the percentage of patients choosing facilities of different characteristics by type of chosen facility. "Insurance" shows patients choosing a facility owned by their insurance, "Doctor" shows patients choosing a facility where their Doctor works.

Figure A6: Quality rankings



Note: "Adjusted" shows risk-adjusted share of treatments that reach adequate URR levels, at the facility level. "Unadjusted" shows raw share of treatments that reach adequate URR levels, at the facility level. "Independent" represents private facilities non-associated with insurance companies. "Public" represents public facilities. "Private" (the omitted category) represents facilities owned by private insurance companies.

Table A1: Acquisitions and management agreements

Year	Facility	Chain	Province
2001	Intir	Diaverum	Montevideo
2001	Crani Lagomar	Diaverum	Canelones
2001	Crani Minas	Diaverum	Minas
2001	Crani 33	Diaverum	Treinta y Tres
2009	**Renis**	**Diaverum**	**Montevideo**
2011	Seine*	Diaverum	Montevideo
2011	Senniad**	Diaverum	Montevideo
2011	Cenepa	Ceneu	Canelones
2012	Unedi	Diaverum	Canelones
2013	**Cedina**	**Ceneu**	**Montevideo**
2015	**Asoc Esp*** **	**Ceneu**	**Montevideo**
2017	Ceter	Diaverum	Maldonado
2017	Canimel	Ceneu	Cerro Largo
2018	Sedic	Ceneu	Montevideo
2018	INU	Ceneu	Montevideo
2023	Comeca***	Diaverum	Canelones
2023	Uruguayana***	Ceneu	Montevideo

Note: Each row represents one acquisition or management agreement. In bold: adult hemodialysis 2003-2017 in Montevideo. *Peritoneal dialysis. **Pediatric dialysis. ***Management agreement.

Table A2: Means and SD of quality measures

	Unadjusted		Adjusted	
Urea Reduction Rate	0.75	(0.15)	0.75	(0.14)
No complications	0.86	(0.07)	0.87	(0.06)
Hemoglobin	0.73	(0.12)	0.73	(0.12)
Kt/V	0.83	(0.12)	0.83	(0.11)
Septic infection	1.00	(0.01)	1.00	(0.01)
Survival	0.99	(0.01)	0.99	(0.01)
Urea	0.85	(0.07)	0.84	(0.07)

Note: "Adjusted" shows risk-adjusted share of treatments that reach adequate URR levels, at the facility-year level. "Unadjusted" shows raw share of treatments that reach adequate URR levels, at the facility year-level. Standard errors in parentheses.

Table A3: First stage of mean decomposition

	(1) Total patients
Quality	16.982**
	(6.118)
Shifts	9.982***
	(0.933)
Stations	3.702***
	(0.319)
Mean stations -j	-4.212***
	(0.483)
Observations	206
CD Wald F	66.182
KP Wald rk F	75.945

Note: "Quality" is risk-adjusted URR. "Stations" is the number the stations at each facility. "Mean stations -j" is the mean number of stations at other facilities. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A4: First stage of marginal cost function estimate

	(1) Quality	(2) Quality	(3) Quality	(4) Quality
Proportion with diabetes	1.840***	1.284***	1.069***	0.957***
	(0.161)	(0.158)	(0.147)	(0.149)
Proportion with cardiopathy	0.824***	1.035***	1.147***	1.278***
	(0.163)	(0.151)	(0.139)	(0.145)
Independent		0.229***	0.258***	0.143***
		(0.028)	(0.028)	(0.034)
Public			0.164***	0.165***
			(0.028)	(0.029)
Chain 1				0.191***
				(0.045)
Chain 2				0.058
				(0.040)
Observations	219	219	219	219
CD Wald F	1,163.075	799.554	686.903	765.400
KP Wald rk F	1,869.890	906.528	713.479	824.275

Note: "Proportion with diabetes" is the proportion of patients with diabetes at a facility. "Proportion with cardiopathy" is the proportion of patients with cardiopathy at a facility. "Independent" represents private facilities non-associated with insurance companies. "Public" represents public facilities. "Private" (the omitted category) represents facilities owned by private insurance companies. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A7: Example of quality disclosure

FONDO NACIONAL DE RECURSOS
Medicina Altamente Especializada

FONDO NACIONAL DE RECURSOS

Programa de Presentación de Resultados

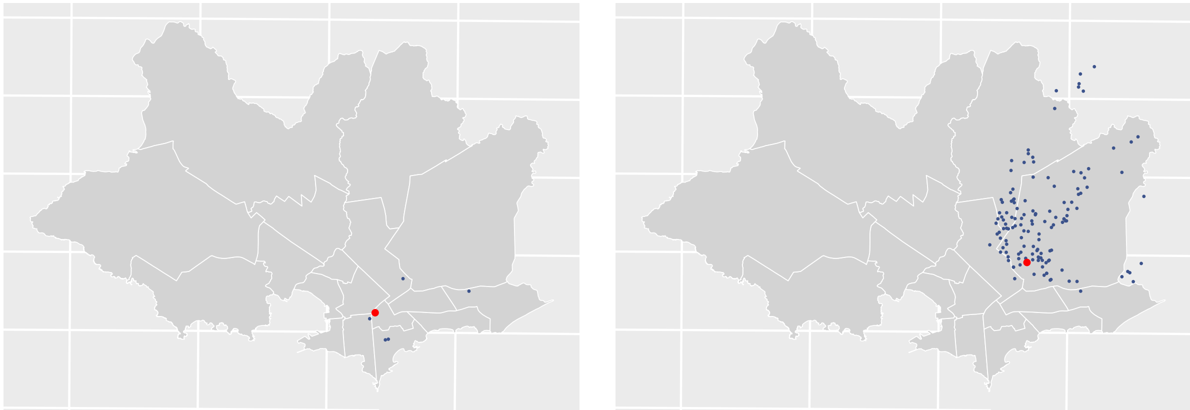
Centro de Hemodiálisis Hospital Británico (Montevideo). Año 2021

Los resultados de cada IMAE se comparan con los obtenidos en el total de la población en tratamiento a nivel nacional con cobertura del FNR en el mismo año. Para las variables que lo requieren, se estableció un "límite de aceptabilidad" que toma en cuenta las recomendaciones que se encuentran en la literatura especializada así como el contexto nacional.

Características generales	**HBritánico**	**Media nacional**
Total de pacientes al 31/12/2021	48	2627
Edad promedio (años)	67	62,62
Diabéticos (%)	31,3	35,5
Calidad de la diálisis	**HBritánico**	**Media nacional**
Pacientes con Kt/V≤ a 1,3 (%)	15,2	17,9
Diferencia promedio pesos corporales post diálisis- pesos "objetivo" de cada paciente	0,7	0,6
Pacientes con urea en sangre ≥ 1,7 mg/l (%)	12,5	6,7
Pacientes con fósforo en sangre ≥ 5,5 mg/l (%)	50	43
Pacientes con PAS < 140 mm Hg (%)	33,3	30,1
Pacientes con hemoglobina en sangre ≤10 g/l (%)	2,2	13,3
Reacciones pirogénicas (cada 1000 procedimientos)	0,57	0,33
Mortalidad	**HBritánico**	**Media nacional**
Mortalidad estandarizada por mil pacientes expuestos	78	133

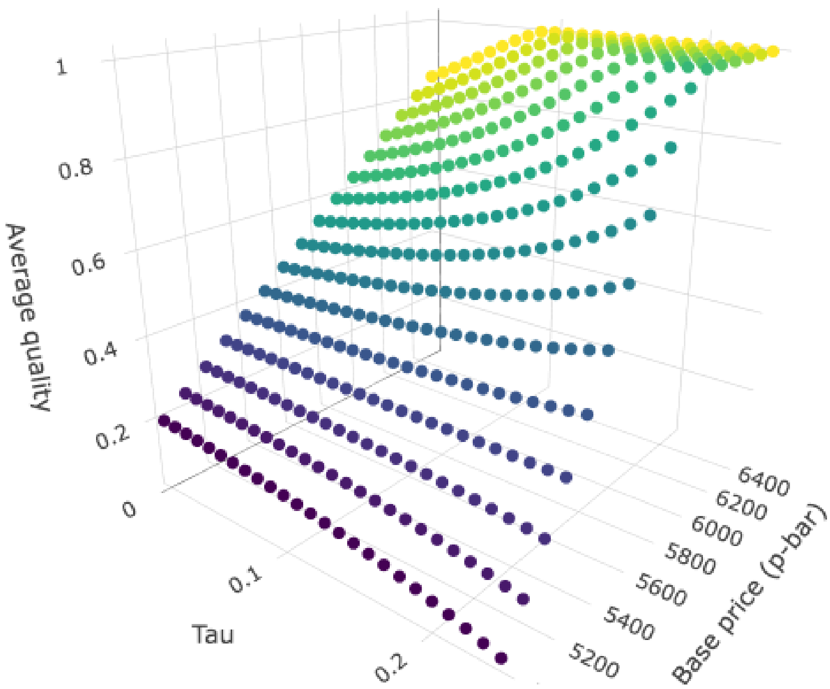
Note: Screenshot of pdf posted on the FNR website. One of this is posted for each facility-year. Retrieved from www.fnr.gub.uy/wp-content/uploads/2022/12/dialisis_hbritanico_2021.pdf, 09/2024.

Figure A8: Non-equilibrium simulated move



Note: "Simulated" shows predicted patient entry count based on the moved facility new location. "Predicted" shows predicted patient entry count based on current facility locations. Red dots indicate facility location, blue dots indicate patients homes.

Figure A9: Counterfactuals grid



Note: Each point represents an equilibrium outcome under different price parameters. Base price ($\bar{p}$) is the baseline level of the pay-for-performance payment scheme. Tau (τ) is the reward/penalty parameter for departing from the set quality threshold. Average quality represents the average proportion of treatments supplied with adequate URR across facilities.

Appendix B: Heterogeneity in patient choice

In this appendix, I use descriptive evidence to explore the role of different drivers of demand for different subsamples of patients.

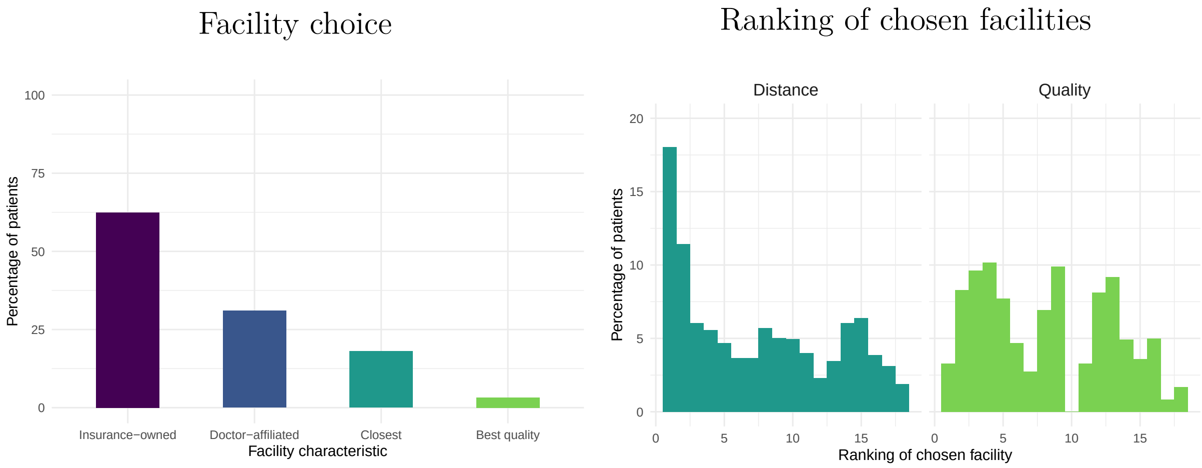
Among patients attending different facility type (Figures B1 to B3), patients who attend private and independent facilities disproportionately choose facilities closer to their home, while patients attending public facilities do not seem to have such preference. This is related to the fact that almost all patients attending public facilities come from public insurance, so they seem to be choosing based on that rather than distance. It is worth noting that in the case of independent facilities, patients seem to be trading-off distance and quality very starkly; lower quality facilities seem to be chosen more than highest quality ones.

Although almost 100% of patients attending public facilities come from public insurance (Figure B5), little over 50% of patients from public insurance attend public facilities. This seems very likely related to capacity constrains in public facilities (Figure 3). This fact may explain why a very high percentage of patients from public insurance attend independent facilities (Table 4). Patients from private insurance seem to be choosing facilities associated with their insurance in more than 60% of cases (Figure B4). They also seem to be choosing distance over quality even more frequently than patients from public insurance.

More sophisticated patients may have different choice patterns than more sophisticated ones. Patients with less than Secondary education are the majority of the sample (Table 4), and do not seem to be choosing very differently than patients with Secondary education or more (Figure B7). Patients with Secondary attend their nearest facility more often and do not seem to choose higher quality more often (Figure B6).

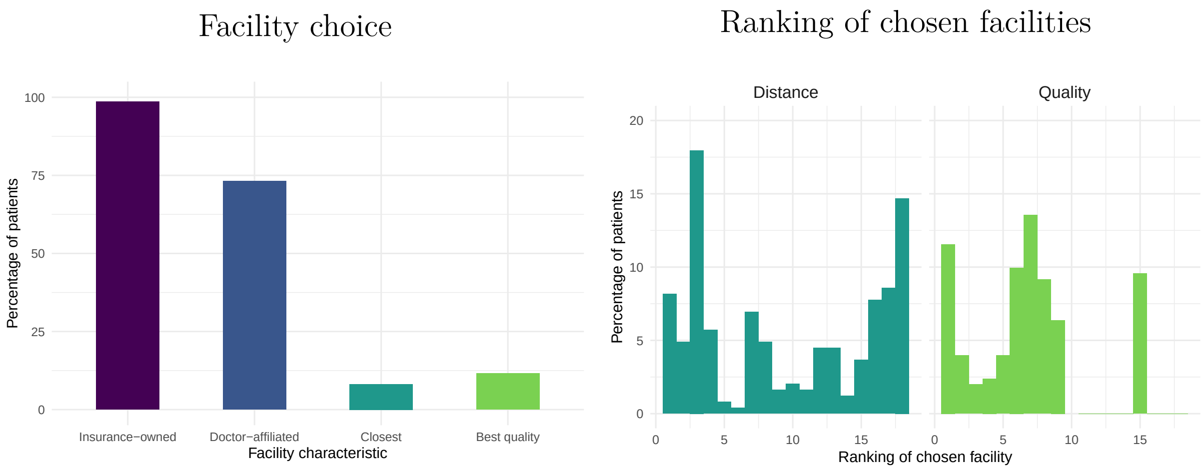
Low mobility is definitely one of the unobservable factors influencing patient choice. However, in comparing patients according to their capacity (Figure B8 and Figure B9), I show descriptive evidence that fully capable patients choose almost identically to not fully capable ones. If anything, fully capable patients seem to be choosing closer facilities more than not fully capable ones.

Figure B1: Patients attending private facilities



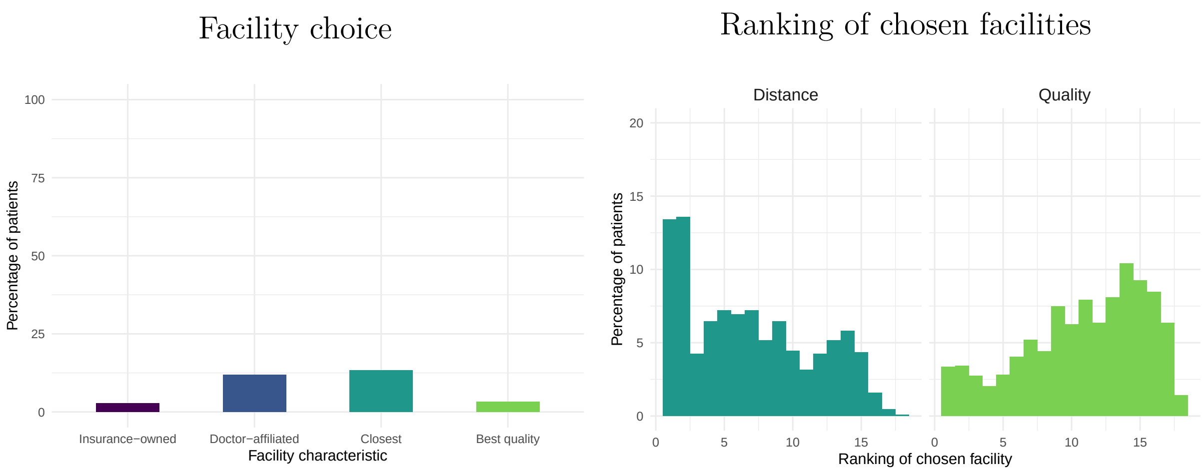
Note: Patients entering dialysis 2003-2016 in Montevideo. The figure plots the percentage of patients choosing facilities of different characteristics.

Figure B2: Patients attending public facilities



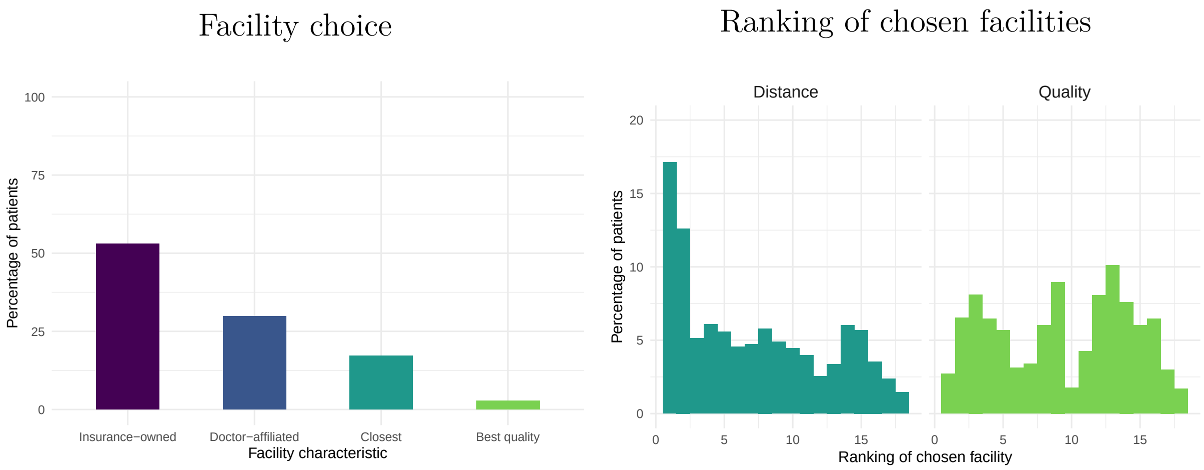
Note: Patients entering dialysis 2003-2016 in Montevideo. The figure plots the percentage of patients choosing facilities of different characteristics.

Figure B3: Patients attending independent facilities



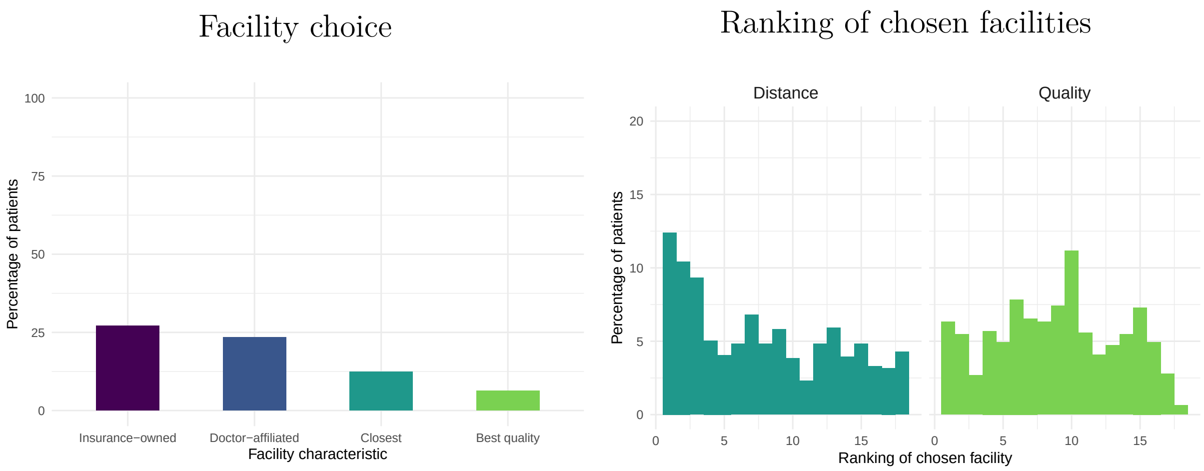
Note: Patients entering dialysis 2003-2016 in Montevideo. The figure plots the percentage of patients choosing facilities of different characteristics.

Figure B4: Patients attending private insurance (IAMC/IAMPP)



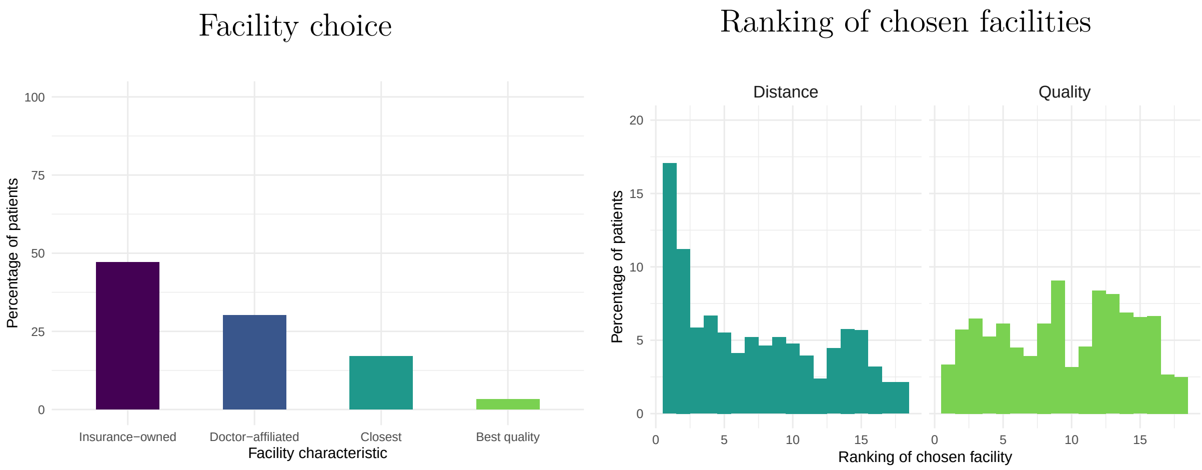
Note: Patients entering dialysis 2003-2016 in Montevideo. The figure plots the percentage of patients choosing facilities of different characteristics.

Figure B5: Patients attending public insurance



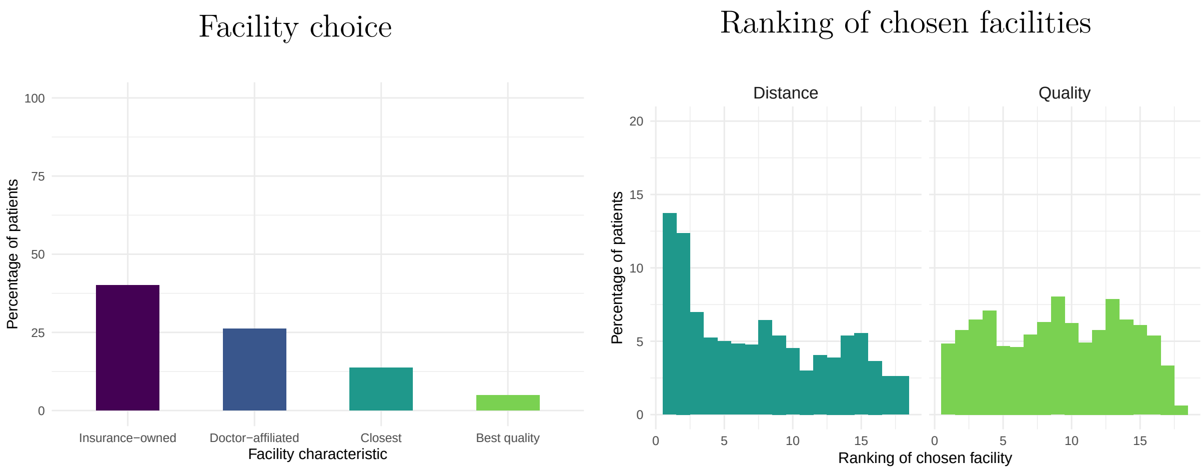
Note: Patients entering dialysis 2003-2016 in Montevideo. The figure plots the percentage of patients choosing facilities of different characteristics.

Figure B6: Patients with Secondary or more



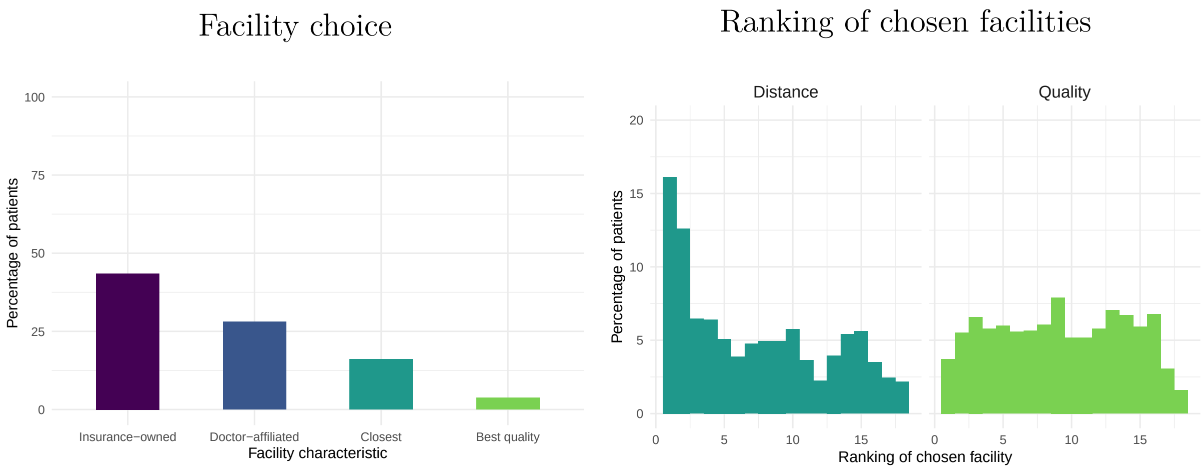
Note: Patients entering dialysis 2003-2016 in Montevideo. The figure plots the percentage of patients choosing facilities of different characteristics.

Figure B7: Patients with less than Secondary



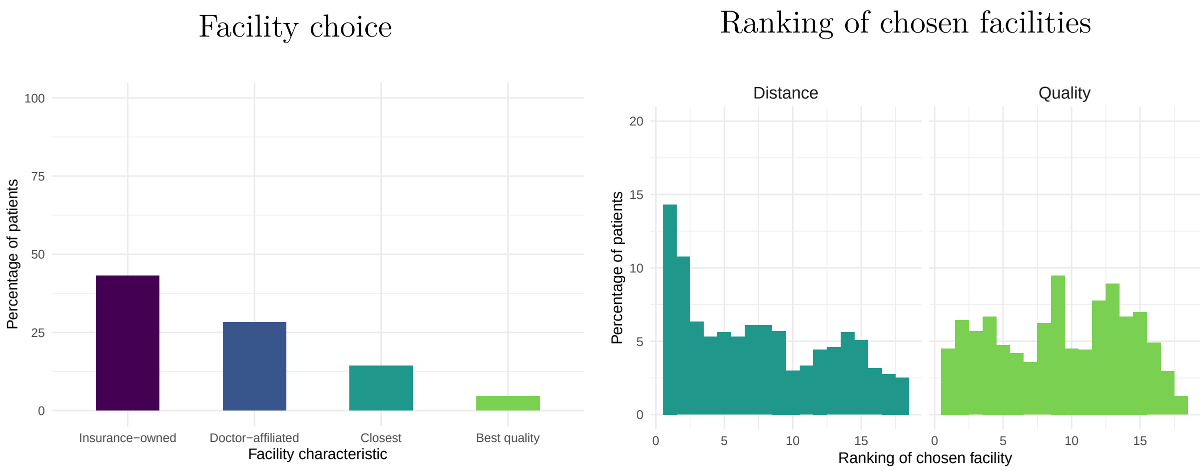
Note: Patients entering dialysis 2003-2016 in Montevideo. The figure plots the percentage of patients choosing facilities of different characteristics.

Figure B8: Fully capable patients



Note: Patients entering dialysis 2003-2016 in Montevideo. The figure plots the percentage of patients choosing facilities of different characteristics.

Figure B9: Not fully capable patients



Note: Patients entering dialysis 2003-2016 in Montevideo. The figure plots the percentage of patients choosing facilities of different characteristics.