Patients' and Providers' Incentives in Out-of-Network Emergency Visits[††]

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Abstract

Insurance coverage for emergency care is the subject of a highly contentious debate. Current legislative action in the U.S. aims to dramatically change the way emergency visits are covered when providers are out of the network of the insurance plan. In this paper, we study the workings of the Chilean insurance coverage for emergency care, which tightly resembles the proposals for the U.S. We study how patients and hospitals respond to the incentives created by the system, and evaluate outcomes and expenditures under different counterfactual arrangements.

Keywords: Emergency, Out-of-network billing, hospitals.

JEL classification: H51, I11, I13, I18

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1 Introduction

Should a patient with a heart attack be charged more for rushing to the closest emergency room instead of going to the one in her insurance plan? The answer to this question varies by country, and is the subject of an ongoing policy debate. In the U.S., 39 percent of individuals are covered with a health plan that covers fewer than 70 percent of the hospitals in their rating area, and roughly half of the plans in the individual health insurance Marketplace grant in-network access to fewer than 25 percent of the physicians in the plan service area (McKinsey Center for U.S. Health Reform, 2015; Polsky et al., 2016). This arrangement has lead to large and unexpected bills for individuals seeking emergency care, which has ultimately spurred a series of proposals to regulate out-of-network coverage in the emergency department (ED) (Cooper and Scott-Morton, 2016; Cooper et al., 2017). The issue of out-of-network emergency coverage is likely to become even more pressing considering the growing importance of narrow-network plans in recent years (McKinsey Center for U.S. Health Reform, 2017).

This paper studies the strategic behavior of hospitals and patients in the provision of out-of-network private emergency care. In particular, we aim to study how patients and hospitals respond to the incentives created by the system, and analyze the welfare consequences of alternative policies.

Our context of study is the Chilean public health insurance system. This setting is particularly relevant for the current policy and academic debate in the U.S., because it tightly resembles the proposals suggested to reform the U.S. system of ED coverage. The Chilean public insurer covers out-of-network ED visits (i.e., visits to private providers) as in-network visits until the patient is stabilized and deemed eligible to be transferred to an in-network (public) provider. After patients are stabilized at the out-of-network provider, they have the choice to either be transferred in-network, or to stay out-of-network with out-of-network prices and coverage rates. These two features closely match the Cassidy-Hassan bill and the Alexandre-Murray bill, the leading proposals to regulate out-of-network ED charges in the U.S.

The goal of this paper is to study the strategic responses of patients and hospitals to the incentives created by the Chilean system of ED payments. In-network coverage for out-of-network ED permits timely and affordable treatment, but is expensive. Under the current system, the Chilean government spends roughly 13 thousand dollars for each out-of-network ED episode. To put this figure in context, Medicare spends almost the same amount during the *12 months* after an inpatient admission. It is unclear to what extent this expenditure is efficient and, in particular, the extent to which the large costs are due to strategic reactions by patients and hospitals. Our model serves to compute outcomes under alternative payment schemes, which will help us understand the role of payment schemes and strategic reactions in generating inefficiencies in the Chilean ED system. This understanding will also allow us to inform the current U.S. debate.

Our paper also aims to contribute to the debate regarding the privatization of health care provision of publicly-insured patients. Although such outsourcing is generally expensive, the extra cost for the public payer may be compensated with significantly higher valuation for the private providers. Our dataset and institutional framework provides us with a rare opportunity to estimate patient's extra valuation for private medical attention and to quantify the welfare consequences from outsourcing.

In the first part of the paper, we study the behavior of hospitals before the patient is stabilized and, specifically, how the intensity of the pre-stabilization treatment in private, out-of-network providers responds to the payments made by the public payer. To this aim, we develop a simple model for the hospital's problem of choosing a patients' length of stay (as in Eliason et al., 2018) as a function of payments from the public insurer. The model sheds light that the quantities and prices observed in the data corresponds to the intersection of two curves that determine the equilibrium; (1) The hospital's "revenue function", which links total payments to the number of hours the patient stays in stabilization, and (2) The hospital's "behavioral function", corresponding to the degree to which hospitals respond to the insurer's payments. Our empirical strategy, based on an instrumental variable approach, allows us to separately identify these two curves.[1]

[1]Since this is a system of simultaneous equations, the identification challenge is akin to the challenge arising in the estimation of supply and demand using market equilibrium data. Our solution is equivalent to finding exogenous shifters of the supply curve and the demand curve to identify the structural parameters of the system.

We find that the “revenue function” in the pre-stabilization period is well described by a combination of diagnosis-based fixed payments with payments at the margin for longer stays. Conditional on patient’s severity, a one percent increase in length of stay increases payments between 0.38 and 0.47 percent. On the supply side, our estimated “behavioral function” implies a price elasticity of pre-stabilization of roughly 0.5, that is, a 1 percent increase in per-hour payments results in a 0.5 percent increase in pre-stabilization hours. Also, our model allows to compute outcomes under alternative payment schemes; for instance, ones that increase the value of the fixed component and decrease the marginal component of payments. We find that this type of scheme may reduce expenses, increase treatment, and increase hospitals’ utility.

The second part of the paper analyzes how the choice of network is shaped by the incentives created by the system. In particular, we study patient’s decisions of whether to stay out-of-network in the post- stabilization phase. Private hospitals generally provide better amenities (and possibly better treatment) than public hospitals. However, stays in private hospitals imply higher out-of-pocket expenses than stays in public hospitals. We leverage detailed information about patient’s characteristics, choices, and length of stay in the post-stabilization period combined with a structural model of demand to estimate patient’s net utility for the private system.

Congestion in public hospitals generate a source of inefficiency in our setting that can be quantified with our demand estimates. As a result of congestion, roughly 80 percent of patients who request a transfer to a public provider after stabilization will remain in the private provider. In those cases, the public payer covers the remainder of the stay in the private hospital at in-network prices. Our simple model shows that low transfer probabilities introduce incentives for patients to declare their intention to be transferred to the public system – even for individuals with low willingness for the private hospital. Case-specific variation in the transfer probabilities and waiting times for transfers generate useful variation in the incentives to stay out-of-network that we exploit in the estimation of the demand model. Our demand estimates are consistent with the theoretical predictions, as we find that individuals with longer expected recovery and lower transfer probabilities are more likely to choose to be transferred.

The model estimates will allow us (in future work) to recover patients’ willingness to pay for remaining in the private hospital and to perform welfare calculations.

1.1 Related Literature

A large body of literature in Health Economics, starting with the landmark RAND Health Insurance Experiment, has shown that patients respond to economic incentives when seeking care (Newhouse, 1993; Manning et al., 1987). This "moral hazard" on the patient side spurred an extensive research agenda on what is the optimal way to provide insurance protection while limiting patient's incentives to overspend (see Gruber (2016) for a review).

Equally important but much understudied until recently is the effect of financial incentives on the decisions of doctors and providers. Clemens and Gottlieb (2014) finds that physicians respond to financial compensation by increasing health provision. In recent work on the hospital side, Eliason et al. (2018) and Einav et al. (2018)) show compelling evidence of strategic reactions to Medicare payments of long term care hospitals. Also, Hackmann and Pohl (2018) show that incentives shape the decisions of patients and providers in the context of nursing homes.[2]

Urgent medical care is different in nature than regular care, as patients in emergent situations are not expected to choose freely to avoid out-of-network providers. In two recent studies, Cooper and Scott-Morton (2016) and Cooper et al. (2017) document the extent of "surprise" billing from out-of-network physicians treating patients in in-network hospitals.

We blend these two strands of literature together as we study patient's and provider's incentives in the context of emergency care. By analyzing a setting where the public insurer contracts with private hospitals, we also build upon the literature studying the interaction between the private sector and the public sector in the provision of health care. Most papers in this literature are concerned with the delivery of public insurance by private firms (see Gruber, 2017; Layton et al., 2019; Cabral et al., 2018; Cutler and Gruber, 1996; Gruber and Simon, 2008; Curto et al., 2019). A few papers analyze the differential responses to government payments between profit and not-for-profit hospitals (Duggan, 2000; Eliason et al., 2018).

[2]Relatedly, Geruso and Layton (Forthcoming) finds evidence that insurers report higher risk levels of their enrollees to receive higher payments from the regulator.

2 Institutional Background

The Chilean health insurance system is divided into a public and a private system. The public regime, "Fondo Nacional de Salud" (FONASA), is a pay-as-you-go system financed by monthly contributions deducted from labor income, cost-sharing, and resources from the government. FONASA covers roughly two thirds of the population (about 11 million people). The private system is a regulated health insurance market operated by a group of private insurance companies known collectively as Isapres ("Instituciones de Salud Previsional"). Isapres cover around 17 percent of the population.[3] Health care provision is also divided between public and private providers.

The focus of this paper is the coverage of emergency visits of FONASA patients, which is regulated by law. According to the law, a person who has an urgent medical condition that constitutes a life-threatening danger or is in risk of a serious functional injury is entitled to go to any health provider and receive affordable medical attention. Our study analyzes instances where publicly-insured (FONASA) patients go to a private hospital. Under these "out-of-network" visits, FONASA pays the hospitals' list prices, which are not negotiated.[4] FONASA reimburses directly to the hospital for expenses until the patient is "stabilized", i.e., when it is safe to transfer the patient to a different hospital. After a patient is stabilized, the patient decides to either request a transfer to the public network —which entails a small copay—, or to remain in the private hospital and pay private-hospital prices with a 90% coinsurance rate. The specific destination hospital is based on the patient's county of residence. In particular, each of the 346 municipalities in Chile belong to one of 29 health-care administrative units –that we herein refer to as a 'referral region". Patients are assigned to one of the public hospitals within the boundaries of the corresponding referral region.

Patients who request a transfer are only transferred if there is a bed available in the public network within their referral region. However, due to capacity constrains in the public system,

[3] A small fraction of the population is insured by seven "closed" private insurance companies, which are available only to workers in certain industries; by special health care systems such as those of the Armed Forces, or do not have any coverage at all.

[4] According to conversations with hospital managers, these prices are lower than those paid by private insurers, but much higher than prices paid by FONASA in cases where prices are negotiated before hand.

on average only 22.2 percent of the patients who request a transfer are actually transferred. Still, patients who are kept in the private network waiting for transfer are not financially responsible for the extra cost of the private network, as they are billed as in-network patients regardless of whether they are actually transferred or not. Therefore, out-of-pocket expenditures in the post-stabilization phase only depend on the decision to request a transfer or not, and not on the actual outcome of such request.

Payer reform Before 2015, the payments to private hospitals for the post-stabilization period came from the yearly budget of each referral region. The main goal was to provide incentives for public hospitals to execute the transfers from the private system in a timely manner. However, public hospitals delayed payments significantly, raising complains from the private sector. Starting in January 2015, for the post-stabilization payments came from the general budget of the public insurer (FONASA) –increasing payments to the private sector but strongly reducing the incentives for hospitals bring patients who request transfers. We exploit the change in the payer as a source exogenous variation to the incentives of private hospitals in order to estimate key parameters of the model, as we discuss in more detail in Section 4.1.5.

3 Data

We use administrative data from FONASA. The data contain detailed information on the universe of emergency visits by FONASA patients to private hospitals from January 2015 to June 2018. Key patient-specific variables include a patient ID, age, diagnosis, county of residence, choice of post-stabilization network, discharge destination (discharged home or transferred to a public hospital), and timestamps for arrival, stabilization, and discharge. We also observe the total pre-stabilization payment and post-stabilization payment[5]. The data also include a hospital ID and the type of bed used at admission and during stabilization (e.g., an ICU bed).

Table 1 shows summary statistics of the data. Two facts are particularly noteworthy. First,

[5]In roughly 7 percent of the cases the patient dies before being stabilized. We exclude those cases from our analysis.

Table 1: Summary Statistics

Request	Discharge	Proportion	N	Age	Pre-Stabilization		Post-Stabilization		Full Stay	
					Payment [CLP MM]	Stay [Hrs.]	Payment [CLP MM]	Stay [Hrs.]	Payment [CLP MM]	Stay [Hrs.]
Transfer	All	0.90	29,790	62.61	2.92	47.78	5.33	157.14	8.41	203.70
	Home	0.70	23,338	63.63	3.08	49.57	5.05	160.49	8.13	209.16
	Transfer	0.20	6,452	58.90	2.16	38.05	7.71	138.76	10.73	173.40
Stay		0.10	3,192	65.95	2.60	38.05	3.76	34.17	6.43	72.29
All		1.00	32,982	62.93	2.89	46.77	5.28	144.22	8.34	189.93

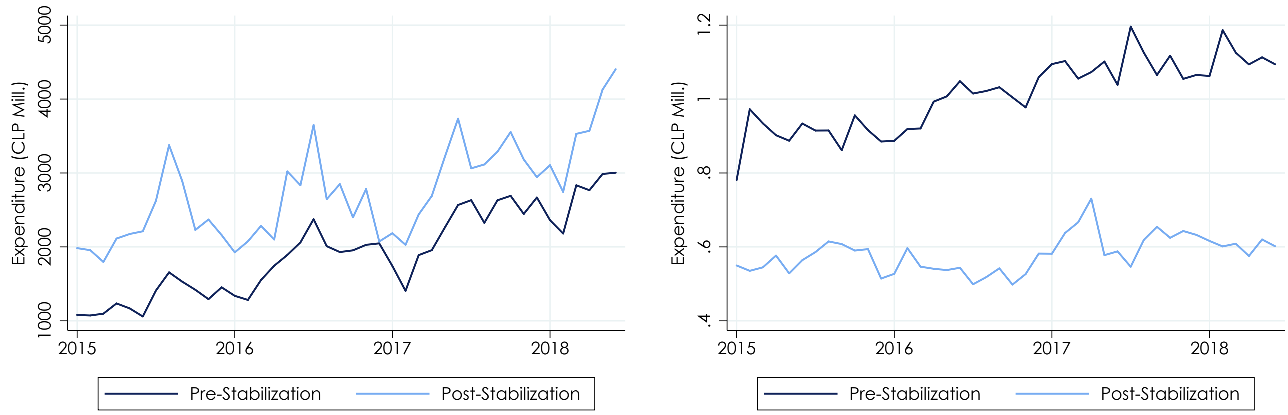
Note: The table shows the average value for patients in each request and outcome pair (USD 1 $\simeq$ CLP 650). Hospital stay is measured in hours.

90 percent of patients requested to be transferred to the public network after being stabilized but only 20 percent were transferred. This means that roughly 80 percent of the patients who requested a transfer to the public network stayed for the entirety of their recovery in the private hospital, and were ultimately discharged home. Second, the cost of these ED visits at private hospitals was large, at CLP 8.41 MM or roughly USD 13 thousand. [6]

Figure 1 shows the time-series evolution of total expenditures (Panel a) and average expenditures per patient-day (Panel b), both for the pre- and post-stabilization phases. Panel (a) shows that total expenditures increased significantly for both phases. Panel (b) shows different sources for these increases. On the one hand, expenses per patient-day have increased for the pre-stabilization phase so that the increases in total expenses is (at least partially) due to the "intensive margin". On the other hand, expenses per patient-day have remained stable for the post-stabilization phase so that the increases in total expenses are attributed to the "extensive margin".

[6] To put this number in context, Doyle Jr et al. (2015) report average Medicare reimbursements to hospitals of USD 7,608 for patients that were admitted through the emergency room.

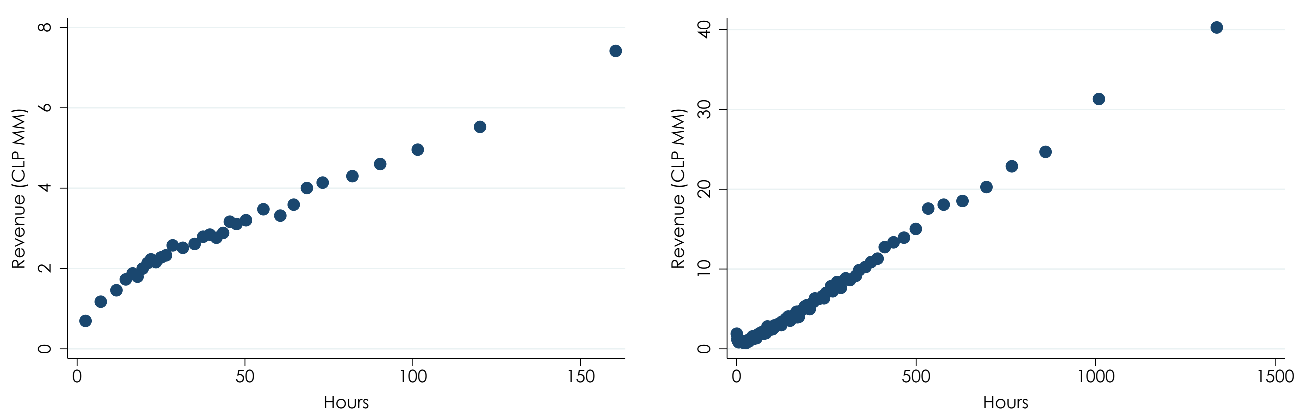
Figure 1: Public System Expenditures



(a) Total Expenditures **(b)** Average Per Patient-Day

Panel (a) and (b) of Figure 2 show binned scatter plots of total revenue per patient as a function of the number of hours spent in the pre-stabilization and post-stabilization phase, respectively. The plots show a slightly concave relationship between hours and revenue in the pre-stabilization period, and linear relationship in the post-stabilization period. We use this empirical fact to support our assumptions regarding the functional form or payments to providers in Section 4.

Figure 2: Hospital Revenues



(a) Pre-Stabilization **(b)** Post-Stabilization

4 Theoretical and Empirical Framework

The main goal of the paper is to quantify how agents' strategic behavior determines the total cost to the public insurer. As noted in Section 2, total costs are the sum of expenses in two different phases: the *pre-stabilization phase* and the *post-stabilization phase*. We develop and estimate a model for each phase.

The pre-stabilization phase corresponds the treatment that occurs immediately after the patient arrives to the ED, up to the point when the patient is stabilized, i.e., deemed to be in sufficiently good health to be transferred to another hospital without compromising her recovery. The strategic agent in this phase is the hospital, which decides how much time should the patient stay until being stabilized.[7] We develop and estimate a simple model for the hospital problem, where the equilibrium length of stay maximizes the hospital's utility.

In the post-stabilization phase, the patient decides whether to stay out-of-network or to request a transfer to an in-network provider. We model the decision regarding the transfer request as a binary choice model in which patients compare the total expected utility under each option. The key insight of this model is that patients' requests for a transfer may not reflect their underlying preferences for in-network v.s. out-of-network care, due to the uncertain nature of the transfer process.

In future work, we will join these two analyses to quantify welfare losses of the strategic behavior of hospitals and patients.

4.1 Supply-side Analysis: The Pre-Stabilization Phase

4.1.1 Theoretical Framework

We follow Eliason et al. (2018) in writing a hospital's objective function for the pre-stabilization phase, π, as the difference between total revenues for keeping the patient q hours $TR(q)$, and a

[7] Arguably length of stay is one of the many inputs that affect hospital's payments as well as patient's outcomes. We focus on length of stay because we do not observe the other inputs.

composite of costs and non-revenue benefits in the pre-stabilization phase, $F(q)$, such that

$$\pi = TR(q) - F(q).$$

The function $F(q)$ incorporates costs, as well as all other non-financial incentives to keep a patient for q hours. The hospital's first order condition is given simply by:

$$TR'(q) = F'(q) \tag{1}$$

We make several functional-form assumptions. These assumptions allow us to closely match the empirical counterparts of the equilibrium objects implied by the model. First, we assume that the payments to hospitals can be characterized by a concave function of hours stayed, such that:

$$TR = a + \beta \times q^{\sigma}. \tag{2}$$

with $a > 0$ and $\beta > 0$ and $\sigma < 1$. This functional form assumption is motivated by the pattern in Panel a) of Figure 2.

Second, we assume that costs and non-revenue benefits, $F(q)$, can also be expressed as a concave function of of hours stayed, such that

$$F(q) = \kappa q + \frac{\gamma}{\omega + 1} q^{\omega+1}. \tag{3}$$

The hospital maximizes utility when

$$\beta \sigma q^{\sigma - 1} = k + \gamma q^{\omega}.$$

Re-arranging terms and using Equation (2) for total revenue, the hospital's *behavioral response* can be written as

$$TR = a + \frac{1}{\sigma}\left(\kappa q + \gamma q^{\omega+1}\right) \tag{4}$$

Equation (4) implicitly defines the optimal level of hours chosen by the hospital as a function of the revenue received.

4.1.2 Discussion and Counterfactual Exercises

Key parameters of this model are β, the elasticity of payment with respect to hours of stay, and a, the fixed component of payments. The relative value of these parameters indicate the extent to which the payment function embeds financial incentives for the hospital to increase the length of stay or not. A payment function with a large β and a low a is akin to a "fee-for-service" payment system, as more care is rewarded with higher payments. On the contrary, a model with a low β and a large a (that, in our empirical application, is diagnosis-specific) is closer to a diagnosis-based payment scheme (like the DRG payments implemented by Medicare).

The goal of the empirical exercise is to quantify the values of β and of a to understand the underlying incentives of the current payment model. Also, with counterfactual analyses we can asses how a change in these parameters would affect outcomes. For instance: Can we lower β and increase a to achieve the same outcomes with lower expenditures? We implement those counterfactuals in Section 4.2.

4.1.3 Empirical Model

The empirical counterparts of the model allow for observed and unobserved heterogeneity. In particular, $TR(q)$ and $F(q)$ depend on patient (i), hospitals (h) and time periods (t), such that equation (2) and (3) can be written as:

$$TR = a_{iht} + \beta_{iht} \times q_{iht}^{\sigma}$$
$$F_{iht}(q) = \kappa_{iht} q_{iht} + \frac{\gamma}{\omega + 1} q_{iht}^{\omega+1}$$

We assume that a_{iht}, b_{iht} and κ_{iht} depend on observables as well as unobservables. In particular, we assume that

$$a_{iht} = \bar{a}_{iht} + \chi_{iht} + \epsilon_{1,iht}$$

$$\kappa_{iht} = \bar{\kappa}_{iht} + \psi_{iht} + \epsilon_{2,iht}$$

$$\beta_{iht} = \bar{\beta}_{iht} + \nu_{iht} + \epsilon_{3,iht}$$

where $\bar{a}$, $\bar{\kappa}$, and $\bar{\beta}$ are the components that depend on observables. The unobserved terms χ_{iht}, ψ_{iht} and ν_{iht} capture shocks that may depend on unobserved patient severity, whereas $\epsilon_{1,iht}$, $\epsilon_{2,iht}$ and $\epsilon_{3,iht}$ are i.i.d shocks.

With these assumptions, the revenue and behavioral function become

$$TR_{iht} = \bar{a}_{iht} + \bar{\beta}_{iht} \times q^{\sigma}_{iht} + u_{1,iht} \tag{2'}$$

$$TR_{iht} = \bar{a}_{iht} + \frac{1}{\sigma}\left(\bar{\kappa}_{iht} q_{iht} + \gamma q^{\omega+1}_{iht}\right) + u_{2,iht} \tag{4'}$$

where $u_{1,iht} \equiv \epsilon_{1,iht} + (\nu_{iht} + \epsilon_{3,iht}) q^{\sigma}_{iht}$ and $u_{2,iht} \equiv \frac{1}{\sigma}(\chi_{iht} + \epsilon_{1,iht})$.

Rearranging Equation (4′) we obtain

$$\frac{TR_{iht} - \bar{a}_{iht}}{q}\sigma = \bar{\kappa}_{iht} + \gamma q^{\omega}_{iht} + u_{2,iht}. \tag{4''}$$

The dependent variable of this equation is either data or estimated parameters and, therefore, is an equation that we can estimate. [8] Equations (2′) and (4″) form the basis of our empirical analysis for the supply side.

4.1.4 Results

We start by showing model-free evidence that higher per-day prices in the post-stabilization phase cause longer pre-stabilization stays. This preliminary exercise also allows us to explain our strategy to identify the elasticity of treatment to prices. In subsection 4.1.5, we provide

[8] In this preliminary version we assume that σ and ω are parameters we already know. In the future, we will estimate them using a minimum distance estimator.

estimates of the supply model following Equations (2′) and (4″).

Let q_{iht} be the number of hours patient i, in hospital h and time t spent in the pre-stabilization phase, and p_{iht} the corresponding per-hour payment. In principle we could estimate, by OLS, the parameters of the following regression:

$$\ln q_{iht} = \chi \ln p_{iht} + \mu_{iht} + \nu_{iht}, \tag{5}$$

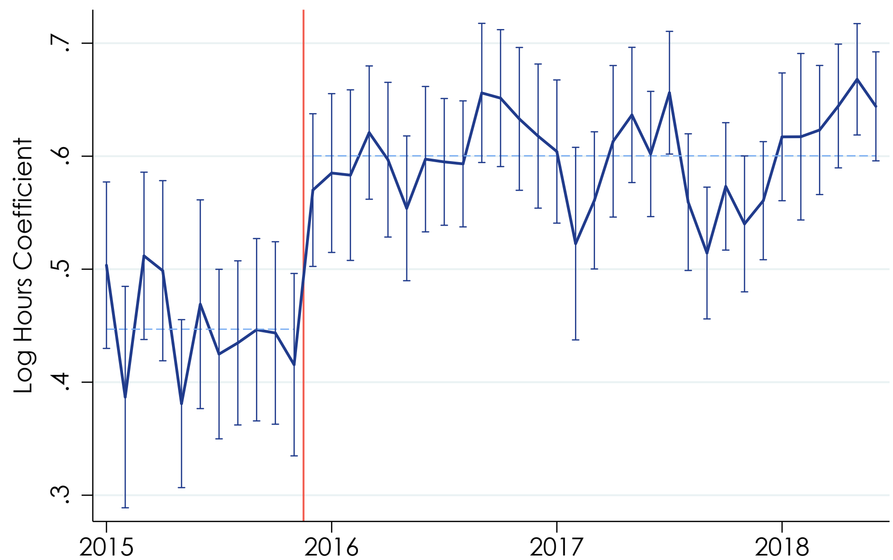
where (in a slight abuse of notation) μ_{iht} represents various fixed effects and ν_{iht} is an unobserved shock.

The OLS estimate of χ in Equation (5) is a biased estimate for the hospital's behavioral response function. The reason is a standard simultaneity bias problem: Equation (5) confounds hospital's reactions with the revenue function, that jointly determine payments and quantities in equilibrium. Intuitively, a hospital behavioral response should dictate a positive relationship between log per-hour payments and log quantity. However, Equation (5) also reflects the revenue function in Equation (2′) —for which the relationship between per-hour payments and quantity depends on the parameters β and σ.

We overcome the identification challenge using a break in the data we observe in the relationship between revenue and hours of stay in December of 2015. This break was due to the payment reform described in Section 2, which gave hospitals more. Evidence for the reform's effect in the data comes from monthly OLS regressions for the elasticity of total payments to stabilization hours. The estimated coefficient for each month is plotted in Figure 3. We find that until November 2015, a one percent increase in post-stabilization hours is associated with a 0.43 percent increase in hospital revenues. In December 2015, this elasticity increases sharply and stays roughly constant at around 0.6.[9] We attribute this sharp change to shocks in FONASA payments that are not correlated with the hospital's choice of q. Thus, we use this break as a shifter of the revenue function that allows us to identify the hospital's behavioral response with a 2SLS estimator.

[9] We also observe a break in the coefficients if we instrument for the endogenous variable as in Equation (6). However, the break occurs in 2016. In future robustness checks we will check the sensitivity of the results to the break date.

Figure 3: Revenue Elasticity over Time



Note: The Figure shows the coefficients and the standard errors of the regression of log payment on log hours during pre-stabilization for each month of the sample. The regression includes hospital, diagnostic and FE. The vertical line indicates December 2015. The horizontal lines indicate the pre and post coefficient averages.

We present the OLS estimates of Equation (4) in Columns (1) to (3) of Table 2. The OLS estimates are negative, contrary to the intuition that hospitals increase the number of hours when per-hour payments are higher. The results of the IV estimation are in Columns (4) and (5) of Table 2, where the instrument is a dummy for the period after December 2015. The IV estimates of χ are positive and consistent with supply-side responses to higher prices. The estimates show a price elasticity of around 0.4, that is, a 1 percent increase in per-hour-payments results in a 0.4 percent increase in pre-stabilization hours.

Table 2: Behavioral Responses

	Dependent Variable: log number of hours in pre-stabilization				
	OLS			IV	
	(1)	(2)	(3)	(4)	(5)
ln price	-0.562***	-0.562***	-0.584***	0.382***	0.400***
	(0.008)	(0.008)	(0.008)	(0.071)	(0.072)
N	25933	25933	25933	25933	25933
AR F-stat				44.45	47.42
AP F-stat				342.81	339.70
Hospital FE	Yes	Yes	Yes	Yes	Yes
Time FE	No	Month	Month-Year	No	Month
Diagnostic FE	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses. Diagnostic FE include first bed, arrival time (5 intervals), death, diagnostic FE. All specifications include day of the week FE. The time FE *Month* means month of the year. * p<0.10, ** p<0.05, *** p<0.01

4.1.5 Estimation

In this section we estimate the parameters of the revenue function and the hospital's behavioral function (Equations (2') and (4")).

4.1.6 The Revenue Function

For patient i in hospital k at time t, we run regressions of the form

$$TR_{iht} = \beta q_{iht}^{\sigma} + \alpha X_{iht} + \delta_h + \rho_t + \epsilon_{iht} \tag{6}$$

where TR and q are, as before, the total revenue in the pre-stabilization phase and the number of hours spent in pre-stabilization phase, respectively; the vector X_{iht} includes observable patient characteristics (diagnosis fixed-effects, arrival time, type of bed). Finally, δ and ρ are hospital and time fixed effects, respectively, and ϵ represents the unobserved component of revenues.

We expect $\beta > 0$, as a longer stay in stabilization, the higher the payments. Moreover, unobserved patient characteristics correlated with time spent and with payment generate an extra source of endogeneity in Equation (6). In fact, we expect that sicker patients (in unobserved ways) generate higher revenue and are also treated for longer period of time. Hence, we expect the OLS estimator of β to be upwardly biased.[10]

We deal with the endogeneity of q in Equation (6) using an instrumental variable (IV) strategy. The goal is to find an exogenous shifter of q that is uncorrelated with unobserved characteristics of the patient. We find that shifter in lagged q, that is, the number of hours spent in the pre-stabilization phase by the previous patient at the same hospital. After controlling for observables, the assumption is that the unobserved health of patient i in hospital h is not correlated with the unobserved health of the previously admitted patient at hospital h. That is, the number of hours that the two patients spend in stabilization is only correlated due to supply side factors. These factors, such as hospital internal practices, congestion, etc., provide a source of exogenous variation in time spent that is arguably uncorrelated with the patient's unobserved severity after controlling for observables.

In this preliminary version, we assume $\sigma = 0.83$, a parameter that fits well the data. Table 3 shows the results of a number of specifications. Columns (1)–(4) show OLS results with a different set of controls. As expected, the OLS estimate decreases as we add control variables. We show the IV results in Column (4). The IV coefficient is lower than the OLS estimates, which is also consistent with our assumption regarding the sign of the bias in the OLS. The Angrist Pischke F-stat is larger than 30, which suggest the instrument is not weak.[11] Columns (5) and (6) show the results before and after the change documented in Figure 3.

[10]Note that $u_{1,iht}$ depends on q

[11]In results not shown in the paper, we find that the coefficients are robust to using week instead of month FE.

Table 3: Revenue Function

	Dependent Variable: log Total Payment					
	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
hours pre$^{\sigma}$	0.093***	0.091***	0.090***	0.047***	0.029	0.052***
	(0.001)	(0.001)	(0.001)	(0.007)	(0.018)	(0.008)
N	26029	26012	26012	24528	5243	19274
AR F-stat				37.46	2.51	36.58
AP F-stat				504.50	79.53	414.58
Diagnosis FE	No	Yes	Yes	Yes	Yes	Yes
Severity Controls	No	Yes	Yes	Yes	Yes	Yes
Service Area FE	No	No	Yes	Yes	Yes	Yes
Time FE	No	No	Month	Month	Month	Month
Sample	All	All	All	All	$<$Dec'15	$\geq$Dec'15

Note: Robust standard errors in parentheses. Severity controls include type of bed, and arrival time (5 intervals). Time FE include month fixed effects. All specifications remove length-of-stays at or above the 99th percentile of the distribution. We assume $\sigma = 0.83$. * p<0.10, ** p<0.05, *** p<0.01

The structure of payments It is instructive at this point to decompose the share of the revenue coming from the fixed payment a, versus the quantity-dependent payments. We do so by calculating the average predicted share, $\hat{a}/\hat{TR}$. We find that the average share of payments corresponding to the fixed component is 65 percent.

4.1.7 Structural Parameters

With the estimates of the previous subsection, we can now estimate the model parameters. In particular, we estimate the revenue function of Equation (2′) and the behavioral response of Equation (4′′). We assume the following structure for $\bar{a}_{iht}$, $\bar{\kappa}_{iht}$ and $\bar{\beta}_{iht}$:

$$\bar{a}_{iht} = a_{h,pre} \times \mathbb{1}(t < \bar{t}) + a_{h,post} \times \mathbb{1}(t \geq \bar{t}) a_{DRG\,i} + a_{first\_bed\,i}$$

$$\bar{\kappa}_{iht} = \kappa_{h,pre} \times \mathbb{1}(t < \bar{t}) + \kappa_{h,post} \times \mathbb{1}(t \geq \bar{t}) + \kappa_{DRG\,i} + \kappa_{first\_bed\,i}$$

$$\bar{\beta}_{iht} = \beta_{pre} \times \mathbb{1}(t < \bar{t}) + \beta_{post} \times \mathbb{1}(t \geq \bar{t}),$$

where $a_{h,pre}$, $a_{h,post}$, $\kappa_{h,pre}$ and $\kappa_{h,post}$ are hospital fixed effects that are allowed to vary before and after the payment reform, $a_{DRG\,i}$, $\kappa_{DRG\,i}$ and $\beta_{DRG\,i}$ are diagnosis fixed-effects, and $a_{first\_bed\,i}$, $\kappa_{first\_bed\,i}$ allow for heterogeneity across the bed type required at admission. Finally, β_{pre} and β_{post} are pre- and post-reform slopes to revenues.

Table 4 shows the model parameters, which include slope estimates that are the same across patients, and individual-specific components.[12] Thus, the rows of the table shows the slope estimates with standard errors, and the average individual components with their standard deviations. Column (1) presents the revenue function parameters, which are the same of Columns (5) and (6) of Table 3. The column indicates that the slope of the revenue function β increased after the payment reform. Column (2) of Table 4 shows the behavioral response parameters, which correspond to the estimation of Equation (4″) with hospital, severity (first bed, time of attention), and month of the year fixed effects.[13] The negative slope γ of the behavioral response indicates that the hospitals' marginal costs and non-revenue marginal benefits increase with respect to the number of hours.

[12] In this preliminary version we calibrate the parameter $\omega = -0.3$, which maximizes the fit of the behavioral response.

[13] The Angrist-Pischke F-stat of this regression is 34.32.

Table 4: Model Parameters

	(1) Revenue Function		(2) Behavioral Response Function
β_{pre}	0.029	γ	-1.625
	(0.018)		(0.265)
β_{post}	0.052	κ	0.594
	(0.008)		[0.095]
a	1.862		
	[1.116]		

Note: Robust standard errors in parentheses. The squared brackets indicate the standard deviation of the parameters in the sample.

4.2 Counterfactuals

In this section we study counterfactual payments in the pre-stabilization period. The goal is to quantify how alternative payment schemes would impact the costs to the public payer considering hospitals' endogenous reactions. For any given value of the structural parameters Θ as well as observable patient characteristics X, we predict the equilibrium $\hat{q}(\Theta, X)$. Then, with the revenue function (Equation 6), we estimate the total revenue under these counterfactual payment policies. In particular, we analyze changes in the relative values of a; the value of the diagnosis-based fixed payments, v.s. β; the marginal payments for longer stays.

Each column of Table 5 shows the result of a different policy, where we increase or decrease a and β by a different factor. We show results for total hours, total revenue, and hospital's utility.

Unsurprisingly, hours, revenue, and utility increase with increases in a (Policy 1 or 2). For instance, increasing a by 20% increases hours by 8%, revenue by 15% and utility by 14% (Policy 1). Even larger increases result from increasing a by 40%. We find similar results after increasing β (Policy 3 and 4). For instance, increasing β by 20 % increases hours by 3%, revenue by 8% and utility by 2% (Policy 3). Even larger increases result from increasing β by 40%. Interestingly, we find policies that decrease revenue but increase utility (Policy 5 and 6). For instance, increasing a by 30 % and at the same time decreasing β by 60 % decreases payments by 1 percent but increases hospital's utility by 15%. Moreover, increasing a by 10 % and at the same time decreasing β by 60 % decreases payments by as much as 15 percent with a marginal increase in hospital's profits. This result shows that alternative payment schedules may generate substantial reductions in payments without harming hospitals. This result is akin to Einav et al. (2018)'s, who find that alternative Medicare payments to long-term care hospitals can reduce payments without affecting hospitals.

Table 5: Counterfactuals

Hours predicted	Baseline	Policy 1	Policy 2	Policy 3	Policy 4	Policy 5	Policy 6
		$\Delta a = 20\%$	$\Delta a = 40\%$	$\Delta a = 0\%$	$\Delta a = 0\%$	$\Delta a = 30\%$	$\Delta a = 10\%$
		$\Delta\beta = 0\%$	$\Delta\beta = 0\%$	$\Delta\beta = 20\%$	$\Delta\beta = 40\%$	$\Delta\beta = -60\%$	$\Delta\beta = -60\%$
Hours predicted	39.16	42.18	45.37	40.22	41.38	40.42	37.38
	-	8%	16%	3%	6%	3%	-5%
Total Revenue	3.10	3.57	4.04	3.35	3.60	3.07	2.63
	-	15%	30%	8%	16%	-1%	-15%
Total Utility	11.07	12.59	14.18	11.29	11.52	12.69	11.18
	-	14%	28%	2%	4%	15%	1%

5 Demand-side Analysis

In this section we present a model for the behavior of patients after stabilization in the out-of-network hospital. The main goal of this model is to recover individuals' underlying preferences for providers, which will allow us to quantify the excess costs of the system due to patient's strategic behavior, and to predict patients' choices and subsequent costs to the public payer under counterfactual incentives.

5.1 Model

For each day of post-stabilization stay at a hospital of type k, the patient receives a flow utility u_k, where $k \in [IN, ON]$ denotes whether the hospital is in-network or out-of-network.[14]

Depending on the patient's choice, the total recovery recovery time T may be spent fully out-of-network, or partially out-of-network and partially in-network. If the patient requests a transfer after being stabilized, she is scheduled for a transfer after T_r days. If $T_r < T$ the patient stays T_r days out-of-network and $T - T_r$ days in the in-network hospital. Alternatively, if $T_r > T$ the patient will spend the full recovery out-of-network. When patients make the decision of whether to request the transfer or not, they are uncertain about the realization of the recovery time T and the transfer time T_r.

If the individual chooses to stay out-of-network, she has to pay p_H for each of the T days of her stay, where p_H is the daily out-of-pocket expense in the private hospital. [15] Yet, regardless of whether patients are actually transferred to the in-network provider or not, patients who request a transfer face a daily out-of-pocket charge g, where $g < p_H$.

Patients maximize expected utility. The expected utility for not requesting a transfer is

$$V_{req=0} = (u_P - \alpha p_H)\, E[T], \tag{7}$$

where α measures the utility of the numeraire and u_P corresponds to the per-hour utility of staying at the private hospital. The total expected utility for choosing to request a transfer is given by:

$$\begin{aligned} V_{req=1} \;\; = \;\; & \int_T (Pr[T_r < T] \times \{(u_P - \alpha g)\, E[T_r|T_r < T] + (u_u - \alpha g)\,(T - E(T_r|T_r < T))\} \\ & + (1 - Pr[T_r < T]) \times (u_P - \alpha g)\, T) f_T dT. \end{aligned} \tag{8}$$

When the transfer is immediate (i.e. when the distribution of T_r is degenerate at 0) indi-

[14]In setting up the model, we omit patient's subscripts to simplify the notation, although in the empirical application we allow heterogeneity across individuals in some of the model parameters.

[15]The assumption that the hospitals charge a fixed per-day amount is supported by Panel (b) in Figure 2.

viduals decide based on a direct comparison of flow utility net of out-of-pocket expenses, as $\lim_{T_r \to 0} V_{req=1} = (u_u - \alpha g)E[T]$. However, the utility of requesting a transfer relative to not requesting a transfer increases with T_r. In fact, $\lim_{T_r \to \infty} V_{req=1} = (u_P - \alpha g)\, E(T) > V_{req=0}$. Intuitively, as T_r increases, the likelihood of being transferred approaches zero, so that asking for a transfer means lower out-of-pocket expenses while staying in the out-of-network provider. We provide supporting evidence for this prediction in section 5.2.

The model allows us to highlight the main source of inefficiency on the demand side: Unless the distribution of T_r is degenerate at 0, the fraction of individuals who decide to request a transfer to an in-network provider is larger than the fraction of individuals for whom the extra utility of a transfer is higher than the extra out-of-pocket cost. These excessive requests for in-network coverage generate a welfare loss, as in these cases the public payer pays for out-of-network coverage even if the benefit for the patient is lower than the cost.[16]

To take the model to the data, we allow for unobserved shocks to the decision to request a transfer or not, such that individuals decide to request a transfer if and only if

$$V_{req=1} + \epsilon_{req=1} > V_{req=0} + \epsilon_{req=0},$$

Under the assumption that the unobserved shocks are iid and distributed Type 1 Extreme Value, the probability of requesting a transfer has the standard closed-form logit solution, $P_i = 1/\left(1 + exp(V_{req=0} - V_{req=1})\right)$.

In the empirical model, we also assume that $T \sim exp(\lambda_T)$ and $T_r \sim exp(\lambda_{T_r})$. This assumption is consistent with the patterns of the data.[17] With exponential recovery times and transfer times we can show that

$$V_{req=1} - V_{req=0} = -(u_p - u_u) \times \frac{1}{\lambda_T}\left(\frac{\lambda_{T_r}}{\lambda_{T_r} + \lambda_T}\right) + \alpha \times (p_H - g) \times \frac{1}{\lambda_T}, \tag{9}$$

[16] A second moral hazard problem occurs as patients pay only a fraction of the total expenses (in our notation, p_H and g include list prices and coinsurance rates). We abstract away from this issue as our focus is on the specific distortions generated by the ED system.

[17] In Figure A1 of the Appendix we show the Cox-Snell residuals of the recovery/transfer times, which indicate the distribution goodness of fit.

which can be re-expressed as moments of the joint distribution of T and T_r:

$$V_{req=1} - V_{req=0} = -(u_p - u_u) \times E[T]Pr[T_r < T] + \alpha \times (p_H - g)\, E[T]. \tag{10}$$

When $Pr[T_r < T]$ approaches one, a transfer is immediate. Therefore the comparison of utilities boils down to comparing the utility net of out-of-pocket expenses in-network v/s out-of-network. However, when $Pr[T_r < T]$ approaches 0, choosing a transfer saves money, as $p_H > g$. The amount of savings is proportional to the expected recovery time, $E[T]$, so that a higher recovery time increases the probability of choosing a transfer.

Equation (10) provides an estimable model for network choice as long as we have measures for $E[T]$ and $Pr[T_r < T]$. We use a model of "rational-expectations" in the formation of these objects, using the realized outcomes of "similar" individuals. Following Abaluck and Gruber (2011), we construct similar individuals based on unique combinations of observables. In particular, we construct cells based on service area, diagnosis, and month of arrival; and construct the proxy for $\widehat{E}[T]$ as the leave-out mean of the recovery time among individuals in the cell. Similarly, we construct the proxy for $\widehat{Pr}[T_r < T]$ as the leave-out mean of a dummy for transfer among individuals in the cell who requested a transfer.

5.2 Results

We provide results of estimating a logit model based on Equation (10) in Columns (1) of Table 6. The sign of the estimates is consistent with the model's prediction: lower rescue probabilities predict a lower probability of choosing transferred, and higher expected recovery times increase the likelihood of choosing a transfer.

Table 6: Logit results for choosing a transfer request based on a 'rational expectations' model

	(1)	(2)
$\widehat{E}[T]\widehat{Pr}[T_r < T]$	-0.118***	-0.119***
	(0.025)	(0.025)
$\widehat{E}[T]$	0.077***	0.077***
	(0.009)	(0.009)
$log(1 + distance)$		-0.015
		(0.017)

Standard errors in parentheses. The number of observations is 25,513. * p<0.10, ** p<0.05, *** p<0.01

Transfer Cost It seems plausible to assume that a transfer per-se decreases utility, in the sense that individuals incur in a switching costs when is transferred. Transfer costs provide a complementary explanation for the positive correlation between transfer probabilities and the decision to stay in-network.

We expect the transfer cost to depend on patient's characteristics, particularly the travel distance between the out-of-network hospital and the in-network hospital. As a preliminary check for the role of transfer costs, we re-estimate the logit choice model by adding a proxy for distance between the in-network and the out-of-network hospital as an additional control.[18] Column (2) in Table 6) shows the results. We do not find a statistically significant effect of distance on network choice.

5.3 Counterfactuals (TBC)

We sketch the main ingredients of our counterfactual exercises for the demand side of the model. The goal of this section is to study the fiscal consequences of increasing the transfer probabilities, taking into account patient's endogenous reactions.

[18] In practice, we use the log distance between the centroid of the patient's county of residence and the county of the private hospital. We plan to geocode hospitals to construct a more precise measure of distance.

In the Appendix we show that the cost to the public payer of an individual who requests a transfer is equal to

$$C_{req=1} = (p_P - p_U) \times \frac{1}{\lambda_{T_r} + \lambda_T} + p_U \times \frac{1}{\lambda_T}$$

where p_P is the per-day cost of a stay out-of-network for government, and p_U is the cost in-network.

The cost of someone who does not require a transfer is

$$C_{req=0} = (p'_P) \times \frac{1}{\lambda_T}$$

with $p'_P < p_P$ is the cost out-of-network for someone who requests to be transferred out-of-network. Therefore the expected total cost per person is given by

$$C = S(\lambda_{T_r}) \times C_{req=1} + (1 - S(\lambda_{T_r})) \times C_{req=0}$$

where $P(\lambda_{T_r})$ is the share of individuals who choose to be transferred. Our model estimates provides us with all the objects to estimate this cost under counterfactual transfer policies that translate into different values for λ_{T_r}.

Intuitively, increasing the transfer probabilities reduces costs to the public payer in two ways: First, mechanically through lower total payments to the private hospitals and second, indirectly by changing individual's decision regarding whether to ask for a transfer or not. Our model and parameter estimates will allow us to conduct such counterfactual analysis in future work.

6 Discussion and Future Work

Insurance coverage for emergency care is the subject of a highly contentious debate. Large and unexpected bills for individuals in the U.S. seeking emergency care from providers not included in the patients' insurer networks have spurred a series of proposals that seek to regulate out-of-network coverage in the emergency department (ED).

The regulatory bills include proposals that are already in place in other countries. In particular, the Chilean public system has two features that closely match the two leading proposals for the U.S. First, the public insurer covers out-of-network ED visits (i.e., visits to private providers) as in-network visits until the patient is stabilized and deemed eligible to be transferred to an in-network provider. Second, after patients are stabilized at the out-of-network provider, patients have the choice to either be transferred to an in-network (public) hospital, or to stay in the out-of-network hospital with out-of-network prices and coverage rates.

The Chilean system is expensive. An average visit to an out-of-network provider costs 12 thousand US, an amount that is roughly equivalent to an entire year of post-admission expenditure in Medicare.

We show that providers are paid based on a mix of diagnosis-based fixed payments and payments on the margin for more hours, and that these payments at margin provide incentives for the provider to provide higher care. Moreover, we find that counterfactual payment structures can reduce costs without changing hospital's utility.

We then study patient' incentives in the post-stabilization phase. Our model shows that patients have strategic incentives that are miss-aligned with the government's objectives. In particular, the system generates excessive requests for transfers towards the in-network provider. The results of our demand estimation confirm the predictions of the model. Evaluating welfare under counterfactual policies on the demand side is left for future work. Future work will also include a richer demand specification, allowing for private information in the distribution of recovery time.

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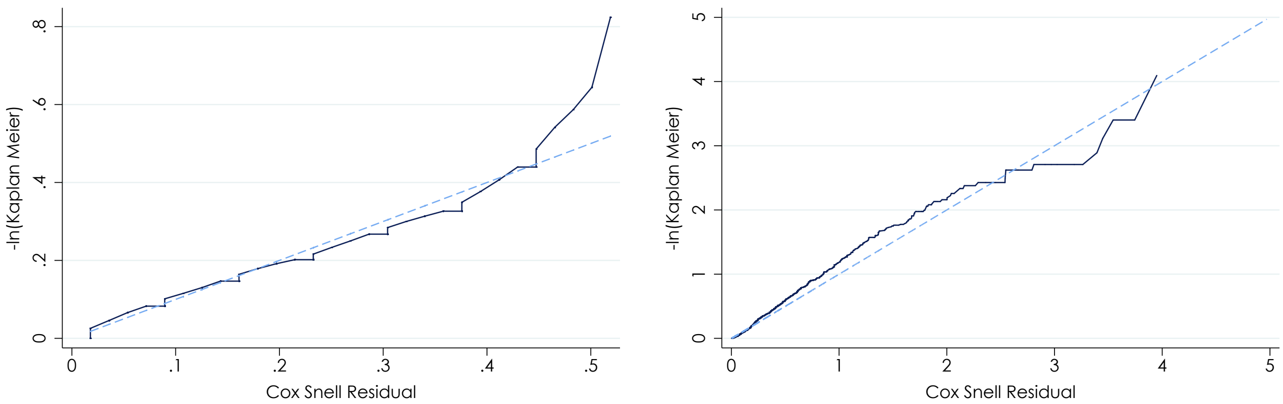
Appendix

A1 Testing the exponential time assumption

The demand model assumes that recovery times and transfer times are exponential. We provide evidence that the exponential distribution provides good fit for the data in figure A1. The figure shows the Cox-Snell residuals ((6) of a an exponential survival models without (Panel a) and with covariates (Panel b) of the total time before discharge.

Figure A1: Exponential Distribution Fit



(a) Unconditional

(b) With Covariates

Note: The figure shows the Cox-Snell residuals of parametric survival models without (Panel a) and with covariates (Panel b) of time to private hospital release. The survival model takes the censoring of the transfer time into account. A perfect fit of the residuals would lie on the 45 degree line (18). We plot time of stay lower than 30 days. Our measuring unit is days. The covariates Panel (b) includes are fixed effects for administrative unit, first bed, and bed required for transfer.