Prompt Payment Enforcement on Framework Agreements for Public Hospitals: Evidence from Chile

Felipe Jordán[a,b]

[a] *Instituto de Economía, Pontificia Universidad Católica de Chile, Vicuña Mackenna 4860, Macul, 7820436, R.M, Chile*
[b] *Instituto para el Desarrollo Sustentable, Pontificia Universidad Católica de Chile, Vicuña Mackenna 4860, Macul, 7820436, R.M, Chile*

Abstract

Demand aggregation through Framework Agreements (FAs) has emerged as a promising tool to support the efficient expansion of affordable healthcare in developing countries. However, the effectiveness of FAs in achieving lower costs may be hindered if prompt payment is not enforced. This paper estimates the impacts of a reform implemented in Chile in 2014, which introduced a prompt payment enforcement procedure in the FAs that supplied public hospitals. Under this reform, firms were allowed to suspend dispatches until overdue bills were paid. The results indicate that hospitals with higher exposure to the reform, measured by their larger share of late bill payments, reduced their payment delays and demand from FAs compared to less-exposed hospitals. Furthermore, the findings suggest that the resulting reduction in the average financial cost of FAs led to a decrease in their prices.

Keywords: Public Procurement, Framework Agreements, Prompt Payment, Health Expenditures, Drugs
JEL: H51, H57, I18.

1. Introduction

Since the turn of the century, developing countries have steadily increased health expenditure, surpassing the pace of economic growth (World Health Organization, 2019). This upward trend has been bolstered by the sustained expansion of public expenditure on health, emphasizing the strategic importance of public procurement of health-related supplies in further advancing access to affordable healthcare and reaching Sustainable Development Goal

3.8 by 2030. The centralization of purchases through Framework Agreements (FAs)—contracts where a set of firms are selected to supply a pool of public agencies under certain conditions for a finite period—has been identified as one of the main tools governments can employ to increase savings in public procurement (Dimitri et al., 2006; Karjalainen, 2011; Fazekas and Blum, 2021; Dubois et al., 2021). Demand aggregation leverages the share size of governments to lower prices, while centralized contracting reduces administrative costs. By providing agencies with cheaper options, FAs save scarce public resources and mitigate corruption risks (Bandiera and Prat, 2009). Even though the benefits of FAs are widely recognized, there are few rigorous quantitative studies evaluating the role of key design features on their performance (Fazekas and Blum, 2021). This paper contributes to filling this gap by estimating the impacts of prompt payment enforcement on the performance of FAs for public hospitals in Chile.

FAs are typically administered by specialized public agencies responsible for estimating aggregate demand, conducting auctions, and selecting winning suppliers. These agreements commonly incorporate two key features: (i) public agencies can procure goods and services offered in the FA either through the FA itself or directly from suppliers, (ii) suppliers are obligated to provide the goods or services to any agency within the agreement at the price set during the auction. The effective enforcement of prompt payment by buyers is essential to ensure the successful realization of cost savings through FAs (Parmaksiz et al., 2022). Without an efficient procedure for enforcing prompt payment, low credit-risk agencies may opt to withdraw from the FA, as firms would charge the average credit risk of participating agencies (Barbosa and Fiuza, 2011). This dynamic has the potential to unravel the FA, as rising credit risk and prices mutually reinforce each other (Jordán, 2014).

This paper studies the effects of the introduction of a prompt payment enforcement procedure in a large set of FAs that supply drugs to Chilean hospitals. Beginning in 2014, firms were permitted to suspend scheduled deliveries to hospitals with outstanding bills until their balances were cleared. Hospitals that paid a larger share of their invoices late before 2014 were more exposed to this new procedure, providing an opportunity to estimate the impacts of stepping up prompt payment enforcement. Three main impacts are hypothesized: Firstly, it is expected that hospitals with higher exposure to the enforcement procedure will reduce their average payment delays, defined as the number of days between invoice reception and payment. Secondly, these hospitals are anticipated to reduce their demand from FAs compared to less-exposed hospitals. Lastly, it is expected that prices will exhibit a more pronounced decline for drugs purchased in larger quantities by the more exposed hospitals.

Exposure to prompt payment enforcement is measured as the fraction of invoices that were paid late before 2014. Given that payment delays and the fraction of late payments are summary statistics drawn from the same distribution, the specification used to test the impact of strengthening prompt payment enforcement on average payment delays takes into account the mechanical correlation between both variables. The results reveal that prompt payment enforcement led to a larger reduction in average payment delays in hospitals that were more exposed.

A standard difference-in-difference specification is used to estimate the impact of prompt payment enforcement on hospitals' demand from FAs. The results indicate that there was a larger reduction in the probability of purchasing a drug through FAs in hospitals that were more exposed.

To estimate the impact of prompt payment enforcement on prices, the empirical strategy leverages the variation between drugs based on their relative demand from hospitals that had a higher share of late invoice payments initially. Using a difference-in-differences specification and employing the weighted average of late payments among buyers of a specific drug as a measure of treatment intensity, the analysis suggests there was a larger reduction in prices in drugs that were more exposed.

Extant literature in economics and health has assessed the impact of pool procurement on drug prices. The health literature has found consistent savings from pooling procurement (Seidman and Atun, 2017). In a recent study, Dubois et al. (2021) find savings from pool procurement across a broad range of drugs in seven low- and middle-income countries, providing strong support to the empirical relevance of pool procurement in reducing health costs.

This paper joins a growing body of research that focuses on how the design of FAs impacts their potential to realize savings (Albano and Sparro, 2010; Barbosa and Fiuza, 2011; Jordán, 2014; Gur et al., 2017; Parmaksiz et al., 2022). Albano and Sparro (2010) note that heterogeneity across public agencies, such as their capacity to pay promptly, may lead to adverse selection. In contrast to Akerlof (1970)'s lemons, adverse selection does not emerge from information asymmetries but from rules that preclude firms from charging agencies deferentially on dimensions that impact their costs. Barbosa and Fiuza (2011) show that federal agencies in Brazil pay higher prices when State agencies (which pay later on average) join a FA, providing support to the hypothesis that firms charge the average credit risk of agencies in FAs. Jordán (2014) develops a static formal model to show that, if firms are not allowed to charge agencies deferentially according to their cost of late payment, prompt payers may opt out of the FA, generating an equilibrium where only late payers buy from the FA at higher prices. In addition, as agencies do not take into account the impact of their late payment on FAs' prices, FAs may undermine their incentives to invest in improving their management practices to secure prompt payment. This paper provides what is, to the best of my knowledge, the first estimates of the causal impact of a FA's prompt payment enforcement on buyers' payment delays, demand from late and prompt payers, and prices.

The paper also relates to a growing literature on the impacts of governments' late payments. Checherita-Westphal et al. (2016) show that governments' late payments reduce firms' profits and increase their likelihood of bankruptcy, hampering economic growth in the EU. Barrot and Nanda (2020) show that a policy that accelerated payment for small firms in the US had a large impact on their employment growth. This paper highlights the fiscal impact of prompt payment enforcement on public drug purchases. Thus, policymakers interested in leveraging FAs to efficiently expand access to affordable healthcare should pay particular attention to the enforcement of prompt payment.

The rest of the paper proceeds as follows. Section 2 introduces the institutional context. Section 3 describes the data. Section 4 states the hypotheses and presents the empirical strategy. Section 5 shows the results. Section 6 concludes.

2. Frameworks agreements and prompt payment enforcement in Chile's public hospitals

Hospitals in Chile have the option to procure drugs independently or through Cenabast, a public organization responsible for aggregating demand from hospitals. Each April, hospitals submit their projected quantities of drugs they plan to purchase through Cenabast's FAs for the following year. If the aggregated demand for a particular drug is large, Cenabast conducts a public first-price, sealed-bid auction to procure the drug.

Cenabast operated as a retailer until 2010, conducting auctions, purchasing drugs, storing them, dispatching them to hospitals, and charging hospitals for the costs. However, due to serious operational and financial deficiencies, Cenabast underwent a change in its business model in 2011.[1] Cenabast retained the task of estimating aggregate demand, conducting auctions, and selecting winners. However, it transferred the dispatchment of orders to hospitals to the firms and stipulated that hospitals were to make direct payments to the firms upon delivery. However, it was not until 2014 that Cenabast introduced a mechanism to enforce prompt payment. Firms were then allowed to suspend dispatches of specific drugs to hospitals with outstanding bills for those particular drugs, until their balances were cleared.

To suspend dispatches to a delinquent hospital, a firm requires authorization from Cenabast, which verifies that the client has an overdue bill. A bill is considered overdue after 90 days from the reception of the invoice for most hospitals, with an additional 30 days for EAR hospitals (*Establecimientos Autogestionados en Red*). EAR hospitals carry out complex medical procedures and possess their own legal personality and patrimony. They enjoy ample autonomy to carry out their functions, including defining their procurement strategies and managing their finances. To maintain their status, they must annually submit an extensive list of performance indicators to the Ministry of Health. On the other hand, non-EAR hospitals are smaller, carry out more straightforward medical procedures, and lack independent legal personality and patrimony. While they manage their own procurements, they depend on the Ministry of Health for funding.

Prior to the introduction of a prompt payment procedure, Cenabast's only recourse to enforce payment was to exclude a hospital from the FA entirely. However, this option was never implemented and was arguably a non-credible thread. Excluding a hospital from the system would have caused significant disruptions, likely proving unbearable for the hospital and potentially leading to political backlash. The introduction of a softer prompt

[1]On the operational side, there were serious failures in the logistic chain. Drugs were expiring in the warehouses, and hospitals' orders were rarely delivered on time. On the financial side, Cenabast's accounts receivable (the money owed to Cenabast by hospitals) systematically increased as it failed to enforce prompt payment from hospitals. Consequently, its accounts payable (the money owed by Cenabast to firms) steadily increased as well. A private audit revealed losses of nine million dollars in 2010 due to inefficiencies in the logistic chain. The accounts receivable were quantified at 170 million US dollars, while the accounts payable were quantified at 190 million US dollars (Neely, 2011). These amounts are significant when compared to Cenabast's budget for the same year, which was 13 million US dollars.

payment enforcement procedure offered a more credible means of ensuring timely payment. In this new approach, firms triggered punishments instead of Cenabast (whose role was contractually limited to verifying overdue bills), and the punishment itself was costly but manageable.

3. Data

Hospitals' Purchases Through Cenabast: Data on purchased drugs from Cenebast's FAs between January 2011 and December 2015 were provided by Cenebast. Drugs are identified by their SKU, the most disaggregated level (brands have different codes). 174 hospitals are selected from Cenabast's clients, which have their own financial chiefs and are in consequence responsible for their purchases and payments. Each observation presents information on the quantity purchased of a specific drug offered through one of Cenebasts' FAs by one of Cenabast's clients in a given month, along with the unit price. During the period, selected hospitals bought 1,803 different drugs.

Cenabast's Auctions: Data on Cenabast's auctions between January 2011 and December 2015 were obtained from Chile Compra, the Chilean public agency that coordinates the web platform over which public agencies are required to procure goods and services. The selected auctions include an identifier of the drug in their descriptions, the same used to identify drugs in the database with purchases from Cenabast. 3,557 out of 4,093 auctions include the identifier. These auctions had 8,050 bids placed by 305 firms on 1,341 drugs.[2] The data are collapsed at the auction-drug level, calculating the price as the weighted average of the winning bids, using awarded quantities as weights.

Late Payment: Invoice-level data on public agencies' payments between January 2011 and December 2015 were provided by ChilePaga, a department of the Chilean Budgetary Office that monitors and promotes prompt payment by public agencies. Information from over 2.7 million invoices received by public hospitals' is processed to construct a novel database that describes annual payment behavior for 174 hospitals with their own financial chiefs. For each year, the database shows the average days it took each hospital to

[2]The number of drugs in the auction data is smaller than the number of drugs bought by hospitals because Cenabast can also acquire drugs through direct purchases to suppliers under certain circumstances (e.g. when there is only one supplier).

pay the invoices received during the year, along with the fraction of invoices that were paid late (over 90 days for non-EAR hospitals and 120 days for EAR hospitals). Figure 1 shows a scatter plot with average payment delays and the fraction of invoices paid late in 2013, the year before the enforcement of prompt payment was stepped up. EAR and non-EAR hospitals are shown in blue and red, and the marginal distribution of both variables are displayed at the margins of the plot. While most non-EAR hospitals pay quickly, there is an important number of them that paid a considerable share of their bills late in 2013. EAR hospitals pay much later on average, and even though they have 30 additional days to pay, a larger fraction of them paid a sizable number of invoices late in 2013.

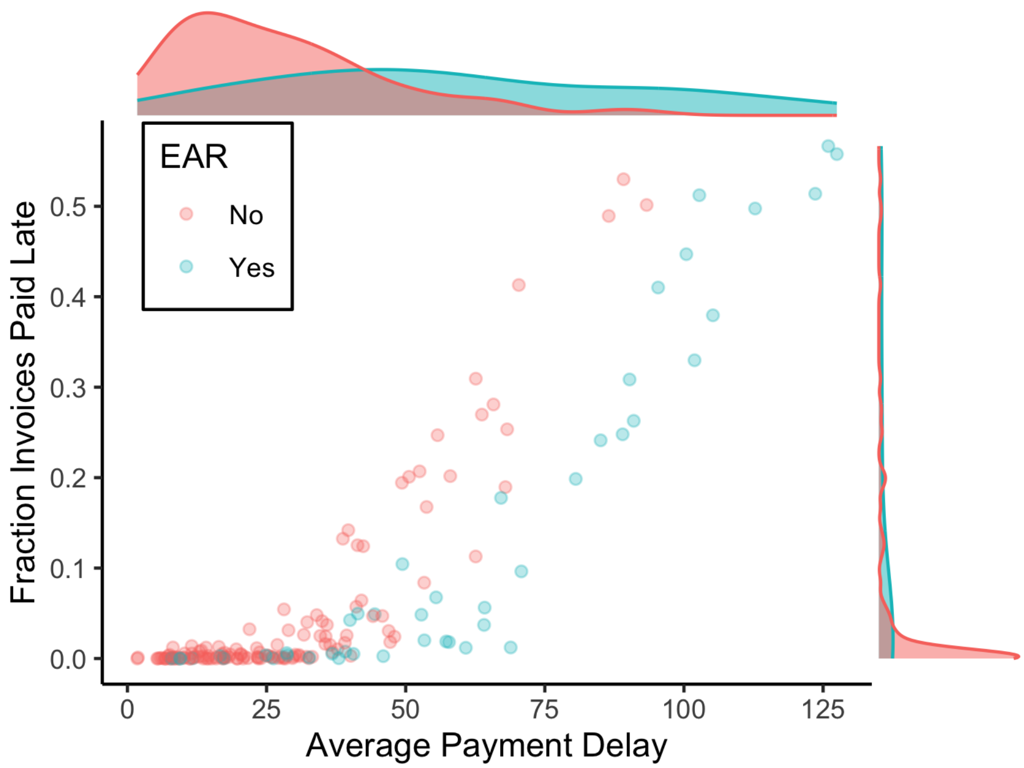

Figure 1: Scatter plot displaying average payment delays (in days) and the fraction of invoices paid late in 2013 for EAR (blue) and non-EAR (red) hospitals. Marginal distributions for both variables by hospital type are displayed at the margins of the plot.

4. Hypotheses and empirical strategy

4.1. Hypotheses

Figure 1 illustrates the significant variation in the fraction of bills that hospitals paid late prior to the reform. It is hypothesized that hospitals with a higher proportion of late invoice payments experienced a greater reduction in their average payment delays. This is because they would face larger losses from the enforcement of prompt payment if they did not modify their behavior:

H1: The proportional fall in average payment delays after 2013 is larger in hospitals that paid a larger share of their invoices late.

As the total cost of purchasing through Cenabast—inclusive of efforts to pay promptly—increased more for hospitals that paid a larger fraction of their invoices late, it is also hypothesized that these hospitals reduced their demand from Cenabast's FAs more:

H2: The proportional fall in demand from Cenabasts' FAs after 2013 is larger in hospitals that paid a larger share of their invoices late before.

Finally, the reduction in payment delays and the shift in demand towards prompt payers rather than late payers are expected to decrease the price of Cenabast's auctions through a reduction of the average credit risk of FAs. Since the auctions of FAs intended to supply hospitals in 2014 were held in 2013, and firms were aware of the forthcoming prompt enforcement procedure to be implemented in 2014, it is hypothesized that drugs that were more intensively demanded by late payers prior to 2013 experienced greater price reductions thereafter:

H3: Drugs that were demanded more intensively by late payers before 2013 experienced larger reductions in their FA's auctions' prices.

Appendix A presents a formal model that formalizes these hypotheses.

4.2. Empirical strategy

This section presents the empirical strategy employed to test each hypothesis. Given that the hypotheses focus on the relative impact of the reform on hospitals or drugs, difference-in-differences specifications are naturally applicable. However, due to specific challenges and differences associated with each hypothesis, separate specifications are presented to address them effectively.

H1: Late payment and average payment delays are summary statistics calculated from the same distribution. Therefore, estimating the impact of prompt payment enforcement on payment delays using the fraction of invoices paid late before the reform interacted with an after dummy variable may yield inconsistent estimates. This is because the dependent variable is mechanically correlated with the definition of exposure to the treatment.

The following specification is used to control for this mechanical correlation:

$$y_{it} = \alpha_i + \alpha_t + \alpha_1 y_{i,t-1} + \alpha_2 Exp_{i,t-1} + \alpha_3 Exp_{i,t-1} \mathbb{1}(t = 2014) + \varepsilon_{it}, \quad (1)$$

where y_{it} is the natural logarithm of the average number of days it took hospital i to pay invoices received in year t, $Exp_{i,t-1}$ is the exposure of hospital i to late payment in year $t-1$, defined as the fraction of invoices paid late in year $t-1$, $\mathbb{1}(t = 2014)$ equals one if the year is 2014 and zero otherwise, α_i and α_t are hospitals' and years' fixed effects, and ε_{it} is a zero-mean disturbance. The parameter of interest is α_3, the effect of exposure on payment delays in the year of the reform vis-à-vis previous years. α_2 captures the difference-in-difference effect for years previous to the reform (only data up to 2014 are included), which controls for the mechanical correlation between exposure in year $t-1$ and late payment in year t. By including a lag of the dependent variable, it is expected that α_2 will capture the regression to the mean of Exp_{it}, that is, the fact that a higher (lower) than average fraction of late payment in year t is, on average, followed by a reduction (increase) in the fraction of late payment and average payment delays.[3]

It is well known that introducing lags of the dependent variable bias estimators when using the traditional within estimator to remove units' fixed effects. To obtain a consistent estimator of α_3, Arellano and Bond (1991)'s estimator is used with a 1-year difference, and $y_{i,t-2}$ as an instrument for $\Delta y_{i,t-1}$.

H2: Exposure for hospital i, Exp_i, is defined as the fraction of invoices paid late in 2013. Data is aggregated at the hospital-drug-year level, and the dependent variable is the physical quantity purchased through Cenabast

[3]A consistent estimation of α_3 does not require the introduction of the lag, as α_2 will capture the bundled effect of the regression to the mean and the autocorrelation structure of the dependent variable if the lag is not included, allowing α_3 to capture the effect of the reform as the residual change in late payment after taking into account the bundled effects. However, it is included in the preferred specification to facilitate the interpretation of the coefficients and increase statistical power.

by hospital i of drug d on year t.[4] Even at this level of aggregation there is a large share of observations that equal zero, so I run two specifications to study both the intensive and extensive margins:

$$\begin{aligned} \mathbb{1}(Purchases_{idt} > 0) &= \beta_{id} + \beta_{dt} + \beta_1 Exp_i After_t + \eta_{idt}, \qquad (2) \\ \log(Purchases_{idt}) &= \kappa_{id} + \kappa_{dt} + \kappa_1 Exp_i After_t + u_{idt}, \qquad (3) \end{aligned}$$

where $Purchases_{idt}$ is the physical quantity purchased through Cenabast by hospital i of drug d on year t, β_{id} and κ_{id} are hospital-drug fixed effects, β_{dt} and κ_{dt} are drug-year fixed effects, and $After_t$ is a dummy that equals one after 2013. Hospital-drug fixed effects control for time-invariant differences between hospitals in their need for different drugs and for drugs' time-invariant differences, such as the unit at which quantities are measured. Drug-year fixed effects flexibly control for differential trends between drugs. The parameters of interests, β_1 and κ_1, capture how the extensive and intensive demand for drugs sold through Cenabast was impacted by the reform in more exposed vis-à-vis less exposed hospitals.

H3: Exposure for drug d, Exp_d, is defined as the average fraction of invoices paid late in 2012 across hospitals that buy drug d, weighted by their demands:

$$Exp_d = \sum_{i=0}^{N} \frac{x_{id}}{X_d} Exp_i, \qquad (4)$$

where Exp_i is the fraction of invoices received in 2012 that were paid late by hospital i, x_{id} is the amount of drug d bought by hospital i during 2012 through Cenabast, and X_d is the amount of drug d bought by all hospitals through Cenabast in 2012. Exposure is defined using 2012 instead of 2013 data (as in hypotheses 1 and 2) because firms placed bids to supply Cenabast's 2014 FAs in 2013, when it was already known that winners would be able to suspend dispatches to delinquent hospitals.

Data is aggregated at the drug-year level, and the dependent variable, p_{dt}, is the average unit price obtained through all auctions where a supplier won a bid on the drug, weighted by the quantities assigned to them. Hence, the following specification is run

[4]While data on demand through Cenabast is available monthly, I aggregate the data at the year instead of month level because hospitals set their order in year t for all months in year $t+1$.

$$\log(p_{dt}) \quad = \quad \gamma_d + \gamma_t + \gamma_1 Exp_d After_t + \nu_{dt}, \tag{5}$$

where $After_t$ equals one after 2012 and zero otherwise, γ_d and γ_t are drug and year fixed effects, and ν_{dt} is a zero-mean disturbance.

Threats to identification: Identification of β_1, κ_1 and γ_1 rely on the traditional parallel trends assumption, i.e. that in the absence of the treatment hospitals and drugs with different levels of exposure to the treatment would have experienced the same growth in the analyzed dependent variables. While this assumption cannot be tested directly, documenting parallel trends before the treatment provides support to the validity of the assumption. $After_t$ is replaced by year dummies in equations 2, 3, and 5 to obtain year-by-year dynamic treatment effects, normalizing the treatment effect at the baseline to zero (2013 for equation 2 and 3, 2012 for equation 5).[5]

A second threat to identification relates to the interpretation of the treatment. Along with stepping up prompt payment enforcement in 2014, Cenabast allowed hospitals to modify their orders for the second semester in $\pm 25\%$ for the first time. As flexibility was not targeted toward prompt or late payers, I expect the effects of flexibility to be captured by years' fixed effects. The results of the theoretical model presented in Appendix A support this interpretation, as flexibility is shown to introduce minor biases to estimators of α_3 and γ_1. In the case of β_1 and κ_1, where the model suggests biases might be larger, the estimators when both prompt payment enforcement and flexibility increase provide conservative estimates (closer to zero) of the estimates that would have been obtained in the absence of an increase in flexibility.

Differential trends between EAR and non-EAR hospitals would also bias the results, as EAR hospitals are, on average, more exposed to prompt payment enforcement (see Figure 1). For this reason, I include in all specifications an interaction between an EAR dummy and year dummies to allow for differential trends between EAR and non-EAR hospitals.[6] By including these interactions, the estimations rely on variations in treatment intensity within EAR and non-EAR hospitals.

[5]Dynamic treatment effects are not feasible for equation 1, as the estimated treatment effect is identified from the relation between exposure in $t-1$ and payment delays in t in 2014 relative to previous years.

[6]For hypothesis 3, I use the fraction bought by EAR hospitals instead of a dummy.

5. Results

Table 1 presents the results of the analysis. To account for the correlation within hospitals and drugs, standard errors are clustered at the hospital level for the first two hypotheses and at the drug level for the third hypothesis. Standard errors are displayed in parentheses below the point estimates.

Columns 1 and 2 show estimates of α_3 and α_2 in the first two rows, when estimating equation 1 without and with a lag of the dependent variable. The sample is limited to the years 2013 and 2014 in both columns, while 2011 and 2012 are used solely to calculate the lags and differences required for the estimations, ensuring comparability between the results.

Estimates of α_3 capture the effect of prompt payment enforcement on average payment delays, after the mechanical correlation between exposure to the treatment in $t-1$ and average payment delays in t has been taken into account by the estimate of α_2. The estimated effect of the reform, shown in column 1, is statistically significant at the 10% level and substantial in magnitude. Considering that the most exposed hospital paid 57% of its bills late in 2013, while the least exposed hospital had no late payments, these findings suggest that the strengthening of prompt payment enforcement reduced the gap in average payment delays between the two hospitals by 0.23 log points (21%).

Column 2 incorporates a lag of the dependent variable using Arellano and Bond (1991)'s estimator to ensure consistent estimation. The point estimate of the lag effect is displayed in the last row. Although not statistically significant, it suggests the presence of positive autocorrelation in average payment delays, which is expected due to unpaid invoices rolling over to the following year. Interestingly, the inclusion of the lag changes the sign of α_2, aligning with the regression to the mean that was expected due to the positive correlation between exposure and the dependent variable (see Figure 1). While the inclusion of the lag does not change the point estimate of α_3, it reduces its standard deviation, making it statistically significant at the 5% level.

The rows $EAR \times Y$ for $Y \in \{2011, \ldots, 2015\}$ present the estimated differential trends between EAR and non-EAR hospitals. Since columns 1 and 2 only include years 2013 and 2014, the estimation is conducted for $EAR \times 2014$, with 2013 serving as the reference year. The results reveal that EAR hospitals exhibited an increase in payment delays compared to non-EAR hospitals, underscoring the importance of controlling for hospitals' types.

Columns 3 and 4 present pooled and dynamic estimates of β_1 of equation 2, reflecting the impact of prompt payment enforcement on the probability of buying a drug through Cenabast. The dependent variable is 100 if a hospital bought a given drug in a given year and zero otherwise. The specification includes fixed effects for the Cartesian product of hospitals and drugs, as well as fixed effects for the Cartesian product of drugs and years. The pooled estimate presented in the first row of column 3 implies that prompt payment enforcement reduced the probability of buying a drug through Cenabast by 8 percentage points ($p < 1\%$) in the most exposed hospital as compared to the least exposed (the coefficient is scaled by the range of exposure, 0.57). Dynamic estimates of the treatment effects presented in column 4 provide support to the parallel trends assumption, with small insignificant estimates for 2011 and 2012. In contrast, estimates scaled by the range of exposure are large and significant in 2014 and 2015, -4.7 and -8.8 percentage points, both significant at the 5% level. Estimates of differential trends between EAR and non-EAR hospitals indicate a consistent reduction in purchases by EAR hospitals compared to non-EAR hospitals over the entire period, confirming the importance of controlling for these differential trends.

Columns 5 and 6 provide the pooled and dynamic estimates of κ_1 of equation 3, which captures the impact on the quantity bought through Cenabast conditional on positive purchases. The estimate in column 5, although not statistically significant at conventional levels, exhibits a large negative value, suggesting that the intensified prompt payment enforcement led to a reduction in demand from FAs at the intensive margin. The dynamic treatment effects in column 6 show stable negative point estimates after the treatment, although large positive point estimates before the treatment call for caution when interpreting these results. No significant evidence of differential trends between EAR and non-EAR hospitals is found in the intensive margin.

Columns 7 and 8 present pooled and dynamic estimates of γ_1 from equation 5, which capture the impact of prompt payment enforcement on the prices of drugs procured through Cenabast's FAs. In 2013, firms were already aware of their ability to suspend dispatches to delinquent clients starting from 2014, implying that the price impacts would likely begin to appear in 2013. Consequently, the $After$ dummy variable takes the value of one from 2013 onwards. The dependent variable is the natural logarithm of the average price of a drug, calculated using all accepted bids by Cenabast in a given year and weighted by the awarded quantities. The specification includes fixed effects for drugs and years.

Although not statistically significant at conventional levels, the pooled estimate displayed in column 7 is negative and large, indicating a poten-

Table 1: Results for tests of hypotheses 1, 2, and 3.

Dep. Var:	**H1**: Payment Delays		**H2**: Purchases				**H3**: Price	
Transformations:	$\log(y)$		$100 \times (y > 0)$		$\log(y)\|y > 0$		$\log(y)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Exp \times After$	-0.57*	-0.57**	-14.2***		-0.16		-0.18	
	(0.30)	(0.26)	(5.4)		(0.11)		(0.35)	
Exp	0.08	-0.29						
	(0.33)	(0.42)						
$Exp \times 2011$				2.3		0.10		0.21
				(4.2)		(0.14)		(0.45)
$Exp \times 2012$				4.6		0.19*		
				(4.0)		(0.10)		
$Exp \times 2013$								-0.31
								(0.30)
$Exp \times 2014$				-8.2**		-0.06		0.17
				(4.0)		(0.12)		(0.86)
$Exp \times 2015$				-15.5**		-0.07		0.10
				(6.4)		(0.15)		(0.50)
$EAR \times 2011$			3.2*	3.0*	-0.07*	-0.08*	-0.00	-0.01
			(1.7)	(1.8)	(0.04)	(0.04)	(0.08)	(0.09)
$EAR \times 2012$			-0.4	-0.8	-0.04	-0.06		
			(1.4)	(1.4)	(0.03)	(0.04)		
$EAR \times 2013$							-0.14**	-0.14*
							(0.07)	(0.07)
$EAR \times 2014$	0.18***	0.16**	-2.9*	-3.4**	0.00	-0.01	-0.39**	-0.40**
	(0.07)	(0.07)	(1.7)	(1.6)	(0.04)	(0.04)	(0.16)	(0.17)
$EAR \times 2015$			-5.7***	-5.6***	-0.01	-0.02	-0.42***	-0.44***
			(2.0)	(2.0)	(0.05)	(0.05)	(0.11)	(0.11)
$\log(y)_{i,t-1}$		0.22						
		(0.14)						
Observations	348	344	455,680	455,680	237,645	237,645	1,768	1,768
Adjusted R2	0.83	-0.08	0.50	0.50	0.94	0.94	0.99	0.99
Fixed Effects	Hospital + Year		Hospital×Drug + Year×Drug				Drug + Year	

Notes: Each column presents point estimates for the dependent variable displayed in the header, with the transformation shown below the variable name. In columns 1 and 2, Exp is equal to the fraction of invoices paid late in year $t-1$ and $After$ equals 1 for the year 2014 and zero otherwise. Only data up to 2014 are included. In columns 3 to 6, Exp is equal to the fraction of invoices paid late in 2013 and $After$ is equal to 1 after 2013 and zero otherwise. In columns 7 and 8, Exp is equal to the fraction of invoices paid late in 2012 and $After$ is equal to 1 after 2012 and zero otherwise. EAR is equal to 1 if the hospital is an EAR hospital and zero otherwise in columns 1-6, and equals the fraction of purchases bought by AER hospital in 2012 in columns 7-8. The fixed effects included in columns 1-2, 3-6, and 7-8 are shown in the last row. Standard errors clustered at the hospital level in columns 1 to 6 and the drug level in columns 7 to 8 are shown below point estimates. * p< 0.1,** p< 0.05, *** p< 0.01.

tial reduction in prices of 0.07 log points (7%) for the most exposed drug compared to the least exposed drug (with an exposure range of 0.38). It is important to note that the large standard deviation of the estimator indicates low statistical power, limiting our ability to detect small effects on prices. As a benchmark, consider that reducing payment delays from 200 to 100 days would result in a decrease in financial costs from 5.3% to 2.6%, assuming an annual interest rate of 10%. Given the low-interest rates during the period and the estimated impacts on payment delays, it is unlikely that the average financial cost of any drug's Framework Agreement was reduced by more than 3%.

The dynamic treatment effects presented in column 8 are imprecisely estimated. While they present no evidence of pre-trends, neither do they offer strong evidence of a negative treatment effect. In contrast, the estimates showing the differential trends between EAR and non-EAR hospitals show that prices of drugs bought more intensively by EAR hospitals experienced large reductions in 2013 and 2014 relative to drugs bought more intensively by non-EAR hospitals, stressing the importance of controlling for hospitals' types.

While I cannot detect the reduction in prices that was hypothesized as a consequence of stepping up prompt payment enforcement, the negative point estimate from column 7, coupled with the robust reduction in payment delays and purchases by late payers, suggests that prices did indeed decrease in response to prompt payment enforcement, although most likely not to the extent suggested by the point estimate presented in column 7.

6. Conclusions

Framework Agreements (FAs) are widely recognized as a promising avenue for reducing procurement costs, particularly in the context of health systems in developing countries. However, the success of FAs in delivering significant cost savings crucially depends on their design. Inadequate enforcement of prompt payment within FAs can lead to prolonged payment delays and an increased proportion of purchases made by late payers, thereby driving up prices and undermining health affordability.

This paper presents, to the best of my knowledge, the first empirical assessment of the impact of prompt payment enforcement on FAs. The study focuses on quantifying the effects of a reform that aimed to strengthen prompt payment enforcement within the FAs of Cenabast, the Chilean public agency responsible for aggregating demand for public hospitals. The reform, implemented in 2014, introduced a provision allowing suppliers of Cenabast's FAs to suspend deliveries to hospitals with outstanding bills. Using a difference-in-difference research design and employing the pre-reform fraction of late payment by hospitals as a measure of treatment exposure, the findings demonstrate that hospitals with higher exposure to the reform experienced reductions in payment delays and FAs' purchases compared to hospitals with lower exposure. Furthermore, the findings offer limited evidence that drugs that were more intensively demanded by late payers exhibited price reductions in comparison to those with greater demand from prompt payers, in line with firms adjusting prices to the reduction of the average credit risk of FAs.

These findings are particularly relevant considering the reform took place during a period of historically low interest rates. As interest rates rise globally, the detrimental effects of inadequate prompt payment enforcement on FAs are expected to become more pronounced. Moreover, it is worth noting that weak prompt payment enforcement might have long-term negative consequences for FAs through unexplored channels, such as its impact on competition in FA auctions. Exploring the relationship between prompt payment enforcement and competition in FA auctions presents an interesting avenue for future research.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author used Chat GPT in order to edit the language. After using this service, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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Online Appendix

Appendix A. Dynamic model of FAs

This section presents a formal model to study the consequences of stepping up the enforcement of prompt payment, and how it interacts with changes in the flexibility with which hospitals can modify their orders to Cenabast. There are two types of institutions that interact through markets and a Framework Agreement coordinated by Cenabast: hospitals and firms.

Appendix A.1. Hospitals

There are N hospitals indexed by i. At the beginning of period t hospitals place orders to purchase x_{ijt} of drug j through Cenabast given inventories I_{ijt}. The needed amount of a drug each period is given by q_{ijt}, a random variable realized after orders x_{ijt} are placed, which follows a uniform distribution between zero and μ_{ij}. However, hospitals can modify their initial orders in $\pm\varepsilon\mu_{ij}$ after the realization of q_{ijt}. Given I_{ijt} and the modified order to Cenabast $x^m_{ijt} \in [x_{ijt} - \varepsilon\mu_{ij}, x_{ijt} + \varepsilon\mu_{ij}]$, inventories in $t+1$ are given by

$$I_{ij,t+1} \quad = \quad \left(I_{ij,t} + x^m_{ijt} - q_{ijt}\right)_+ . \tag{A.1}$$

If $q_{ijt} < x_{ijt} + I_{ijt} - \varepsilon\mu_{ij}$, hospitals roll over inventories at a unit cost of c. If $q_{ijt} > x_{ijt} + I_{ijt} + \varepsilon\mu_{ij}$, hospitals fall short of their needs and must buy the rest in the open market. Otherwise, they exactly match their needs and start the next period with no inventories.

After defining x_{ijt}, hospitals make two irreversible investments that define their payment delays. The first, λ^c_{ijt}, implies that the number of days it takes to pay drug j's purchases from Cenabast follows an exponential distribution with rate λ^c_{ijt}, while the second, λ^d_{ijt}, does the same for direct purchases in the open market. The marginal cost of these investments per purchased unit is constant and equal to a_i. Hospitals differ in their managerial capacity to promptly pay providers, which is reflected in the parameter a_i that increases with hospitals' index, i.

Hospitals know that firms will charge them a price whose present value equals the spot market price p_{jt} when purchasing directly from them. Hence, they select λ^d_{ijt} by solving

$$\Omega^*_d \quad = \quad \min_{\lambda^d_{ijt}} \quad \lambda^d_{ijt} a + p_{jt} \frac{\lambda^d_{ijt}}{\lambda^d_{ijt} - r}, \tag{A.2}$$

where r is firms' daily discount rate.[7]

Firms cannot charge hospitals deferentially according to their payment delays when selling through Cenabast. However, hospitals face expected costs valued at K per dollar paid late (over M days).[8] Hence, they select λ_{it}^d by solving

$$\Omega_c^* \quad = \quad \min_{\lambda_{ijt}^c} \quad \lambda_{ijt}^c a + p_{jt}^c \left(1 + e^{-\lambda_{ijt}^c M} K\right), \tag{A.3}$$

where $e^{-\lambda_{ijt}^c M}$ is the probability hospital i pays drug j acquired through Cenabast in period t in more than M days, and p_{jt}^c is the expected price of drug j through Cenabast in period t, which hospitals' take as given.

Given the value functions of equations A.2 and A.3 and an initial level of inventories, and assuming $\Omega_c^* < \Omega_d^*$,[9] hospitals' Bellman Equation for drug j is

$$\begin{aligned} V(I) \quad = \quad & \max_{x \geq \varepsilon\mu} -\Omega_c^*(x - \varepsilon\mu) + \\ & \int_0^{I+x-\varepsilon\mu} \left[-c(I + x - \varepsilon\mu - q) + \beta V(I + x - \varepsilon\mu - q)\right] f(q)dq + \\ & \int_{I+x-\varepsilon\mu}^{I+x+\varepsilon\mu} \left[-\Omega_c^*(q - I - x + \varepsilon\mu) + \beta V(0)\right] f(q)dq + \\ & \int_{I+x+\varepsilon\mu}^{\mu} \left[-2\varepsilon\mu\Omega_c^* - \Omega_d^*(q - I - x - \varepsilon\mu) + \beta V(0)\right] f(q)dq, \end{aligned}$$

where subscripts have been dropped to simplify notation; $f(q)$ is the density function of q ($\frac{1}{\mu}$ for $q \in [0, \mu]$, zero otherwise); and $\beta < 1$ is hospitals' discount factor. The first summand is the cost of procuring $x - \varepsilon\mu$ through Cenabast; the second is the expected cost of transferring inventories to the following period and the discounted value of starting the next period with positive inventories, conditional on accumulating inventories; the third is the expected value of buying the remaining drug from Cenabast and the discounted value of starting the next period with zero inventories, conditional

[7] Note that $\frac{\lambda}{\lambda+r} = E(e^{rD})$, with D representing payment delays.

[8] K represents the expected cost of actions that may be imposed on hospitals when paying late, such as their exclusion from the Framework Agreement or the suspension of future dispatches.

[9] If $\Omega_c^* \geq \Omega_d^*$, the problem has a trivial solution at $x(I) = 0$.

on q falling within $\varepsilon\mu$ of x; and the fourth is the expected cost of purchasing the remaining drug using the maximum flexibility allowed by Cenabast plus direct purchases to firms and the discounted value of starting the next period with zero inventories, conditional on q surpassing $I + x + \mu\varepsilon$. Intuitively, hospitals trade off a lower unit cost of acquisition through Cenabast with the possibility of buying more than they need for the current period and incurring the cost of accumulating inventories.

Assuming the value function takes the form $V(I) = \alpha + \delta I$, applying the envelope theorem, and calculating the first order condition leads to the following policy function:

$$x(I) = \max\left\{\frac{(1-\varepsilon)(\Omega_d^* - \Omega_c^*) + \varepsilon(c + (1-\beta)\Omega_c^*)}{\Omega_d^* - \Omega_c^* + c + (1-\beta)\Omega_c^*}\mu - I, \varepsilon\mu\right\}. \quad \text{(A.4)}$$

The solution is $x = \frac{\mu}{2}$ when $I = 0$ and $\varepsilon = 0.5$, as in this case hospitals can exactly meet their needs using Cenebast. From that point, the effect of a marginal fall in ϵ depends on what is the larger loss at the tails of the distribution. If the realized value of q is low, the agency must pay the inventory cost and buy the drug today instead of the next period, which leads to a net loss of $c - (1-\beta)\Omega_c^*$ considering the discounted value of marginally increasing inventories for the next period ($V'(I) = \Omega_c^*$). If the realized value of q is high, the agency must procure the drug at an extra cost of $\Omega_d^* - \Omega_c^*$. Hospitals will hedge against the larger cost when ε falls, leading to a positive relationship between ε and x when $\Omega_d^* - \Omega_c^* < c - (1-\beta)\Omega_c^*$ and a negative relationship otherwise. In either case, note that as long as both costs are positive, $x(I) < \mu$.

The expected quantity that will be purchased through Cenabast conditional on x and I is given by:

$$\begin{aligned} E(x^m) &= (x - \varepsilon\mu)\left(\frac{I + x - \varepsilon\mu}{\mu}\right) + 2\varepsilon x + \\ &\quad (x + \varepsilon\mu)\left(\frac{\mu - I - x - \varepsilon\mu}{\mu}\right). \end{aligned} \quad \text{(A.5)}$$

Appendix A.2. Firms

Firms operate in perfectly competitive, open-access markets to produce and sell each drug j at a unit cost κ for direct sales to hospitals and $\kappa - \gamma$

for sales through Cenabast.[10]

Firms are selected to provide Cenebast's FAs through first-price, sealed-bid auctions. After observing hospitals' investment decisions, orders, and inventories, they place their bids.[11] Under these conditions, the expected value of winning a bid with posted price p^c_{jt} for drug j in period t is given by:

$$E(\Pi(p^c_{jt})) \;=\; \sum_{i=1}^{N}\left(p^c_{jt}\frac{\lambda^c_{ijt}}{\lambda^c_{ijt}+r}-\kappa+\gamma\right)E(x^m_{ijt}), \tag{A.6}$$

where λ^c_{ijt} and $E(x^m_{ijt})$ are functions of p^c_{jt}, given by the FOC of equation A.3 and by equation A.5.

Appendix A.3. Equilibrium

An equilibrium in the market of drug j for period t, conditional on initial inventories I_{ijt}, is given by prices p_{jt} and p^c_{jt}, investments in prompt payment λ^d_{ijt} and λ^c_{ijt}, and orders to Cenabast x_{ijt} such that: (i) hospitals minimize their expected cost and (ii) expected profits for firms are zero.

Zero profits in direct sales to hospitals imply $p_{jt}=\kappa$. λ^d_{ijt} can be found by replacing $p_{jt}=\kappa$ in the FOC of equation A.2. As there are closed-form solutions for hospitals' problems, it is enough to numerically find a value of p^c_{jt} for which $E(\Pi(p^c_{jt}))=0$ to find the equilibrium of the Framework Agreement. Note that $E(\Pi(p^c_{jt}=\kappa-\gamma))<0$. Also, there exist $p>\kappa-\gamma$ for which $E(\Pi(p^c_{jt}=p))=0$, because $E(x)=0$ in decreasing in p for all hospitals. Then, the continuity of $E(\Pi(p^c_{jt}))$ secures that there is a unique equilibrium at the lowest price above $\kappa-\gamma$ where $E(\Pi(p^c_{jt}))=0$.

Appendix A.4. Comparative Statics

Cenabast introduced two changes that took effect in 2014: a prompt payment enforcement procedure, and flexibility for hospitals' to modify their

[10] $\gamma\in(0,\kappa)$ can reflect the effect of economies of scale associated to Cenabast's FA large demand. Note that the assumption of perfect competition rules out the alternative possibility of demand aggregation attracting more competition to the auction and hence lowering prices by decreasing firms' rents in equilibrium. Perfect competition is assumed for simplicity, as the focus of this paper in on the buyers side of the market. Hence, γ can also be understood as the not modeled effect of competition in auctions' equilibrium prices induced by demand aggregation.

[11] Observing inventories is only required when an order is ε, since inventories can be inferred from orders otherwise.

initial requests. These changes map to increasing K and e in the model. The model is numerically solved to show that an increase in prompt payment enforcement can be distinguished from an increase in flexibility. While flexibility can have relevant effects on demand and prices, the effects on prompt and late payers are similar. In contrast, as prompt payment enforcement is targeted toward late payers, it has a larger impact on them. As some drugs face more demand from late relative to prompt payers, differential impacts on late payment and demand across hospitals translate to differential impacts across drugs' equilibrium prices.

Figure A.2 shows the results for a parametrization where $M = 90$, $r = 12.5\%$ (annually), $c = 0.03$, $\beta = 0.925$, $\kappa = 1$, and $\gamma = 0.2$. The model is solved for 51 hospitals, 301 drug, and 25 periods, starting with zero inventories in the first period. The first 4 periods are dropped (enough for inventories to converge to their steady state), and the parameters K and e are changed in period 15. Hospitals' marginal cost of paying promptly, a_i, go from 1 to 7 in equidistant steps. Hospitals' maximum possible need for each drug, μ_{ij}, are generated with a normal kernel that picks at equidistant points between drug 1 and 301 following hospitals' indices.[12]

Figure A.2 comprise nine plots, organized in three columns and three rows. In all plots, the x-axis represents periods, with change in the values of k or e happening in period 1 (red vertical dotted line). In the first column, flexibility is unchanged ($e = 0$ in all periods) but enforcement is stepped up (K goes from 0.15 to 0.45). In the second column enforcement is unchanged ($K = 0.15$) but flexibility increases (e goes from 0 to 0.1, 20% of the expected need). In the third column, both enforcement and flexibility increase. The rows present the evolution of different equilibrium variables of interest: the expected average number of days from the reception of the invoice to payment (payment delays) for the hospital with the lowest, medium, and highest value of a (marginal cost of paying promptly); the average expected quantity bought to Cenebast for the same hospitals, normalized by drugs' maximum needs μ_{ij}; and the equilibrium overprice (percentage points above marginal costs) for the drug with the lowest, medium, and highest values of exposure to prompt payment enforcement, defined as the baseline average expected fraction of late payment, weighted by hospitals' baseline average expected

[12]The standard deviation of the normal kernel is equal to a quarter of the number of drug.

demand.

When enforcement is stepped up while keeping flexibility unchanged (first column), the reduction in payment delays is larger for more exposed hospitals (first row). The second row shows a similar pattern for the quantity bought through Cenabast, with larger reductions for more exposed hospitals. Reductions are more pronounced in the first period when enforcement is stepped up, as hospitals adjust to lower desired levels of inventories. The third row shows that these differential effects are reflected in drugs that are deferentially exposed to prompt payment enforcement. While the drug with the lowest exposure reduced its overprice from about 1.8 to 1.0%, the drugs with the medium and highest exposure experienced reductions from 3.0 and 4.4 to 1.4 and 1.8%.

Predictions differ when only flexibility is increased (second column). There are no large changes in the equilibrium price of drugs or average payment delays (rows 1 and 3), but there is a slight increase in the quantity bought to Cenebast across the three hospitals (row 2).

When both enforcement and flexibility are increased, I obtain patterns for prices across drugs and average payment delays that closely follow those obtained when only enforcement is increased (rows 1 and 3). While the pattern for the average quantity bought through Cenebast by the three hospitals is qualitatively preserved, with more exposed hospitals experiencing larger reductions, the differences are quantitatively less striking than when only enforcement is increased.

To check whether these patterns are robust to the model's parametrization, the model is simulated a 1,000 times randomly picking r, c, β, γ, K_1 (enforcement after the reform), and e_1 (flexibility after the reform).[13] In each iteration, the random realization of drug needs, q_{ijt}, are the same across three possible treatments: only enforcement is increased, only flexibility is increased, and both are increased. Then, the following difference-in-difference specifications are run with the simulated data, for each treatment in each

[13] Parameters are drawn from the following uniform distributions: $r = U(0.05, 0.2)$, $c = U(0.01, 0.05)$, $\beta = U(0.86, 0.99)$, $\gamma = U(0.1, 0.3)$, $K_1 = U(0.3, 0.6)$, $e_1 = U(0.05, 0.15)$.

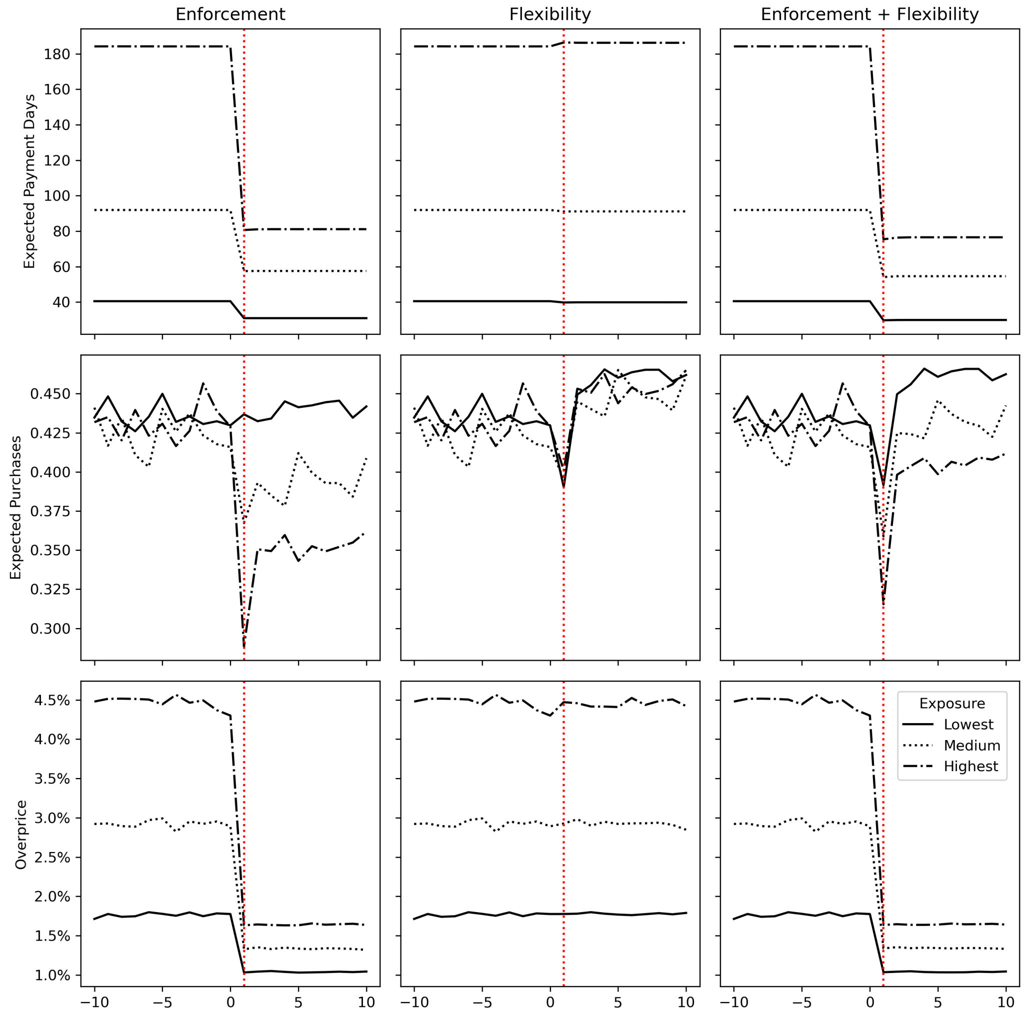

Figure A.2: Evolution of average price, quantity bought through Cenebast, and days of payment before and after the introduction of prompt payment enforcement, demand flexibility, and both

simulation:

$$\log(l_{it}) = \alpha_i + \alpha_1 After_t + \alpha_2 After_t Exp_i + \varepsilon_{it}, \tag{A.7}$$

$$\log(x_{it}) = \beta_i + \beta_1 After_t + \beta_2 After_t Exp_i + \eta_{it}, \tag{A.8}$$

$$\log(p_{jt}) = \gamma_j + \gamma_1 After_t + \gamma_2 After_t Exp_j + \nu_{jt}, \tag{A.9}$$

where l_{it} and x_{it} are average payment delays and average expected purchases through Cenabast across drugs for hospital i in period t; p_{jt} is the price of drug j in period t; $After_t$ a dummy that equals 1 for periods after the changes in K or e take place; Exp_i is hospital i's exposure to prompt payment enforcement, i.e. the expected fraction of purchases paid late by hospital i before K or e change; Exp_j is drug j's exposure to prompt payment enforcement, i.e. the weighted average of late payment among drug i's buyers; α_i, β_i, and γ_j are fixed effects, and ε_{it}, η_{it}, and ν_{jt} are zero-mean disturbances. The parameters of interest are α_2, β_2, and γ_2, representing the differential impact of the treatment on hospitals' payment delays, hospitals' demand from Cenabast, and drugs' prices.

The top-left plot of Figure A.3 shows box plots with the distribution of $exp(\alpha_2) - 1$ when the treatment is enforcement, flexibility, or enforcement and flexibility. These estimates represent the estimated percentage change in hospitals' expected payment delays when moving from zero to one in exposure to stronger prompt payment enforcement. Each box shows the interquartile range (IQR), with whiskers representing the 1^{st} and 99^{th} percentile across the 1,000 simulations. Individual point estimates within these percentiles are displayed as small red dots. The median and mean across simulations are displayed as blue lines and green triangles.

Point estimates are negative and tightly clustered at low values when only prompt payment enforcement changes, with the IQR going from -69 to -52%. The median and average effects are -63 and -60%. When only demand flexibility increases, the dif-in-dif estimates are small and positive, with the IQR going from 3.7 to 7%. When both prompt payment enforcement and demand flexibility increase, estimates are slightly smaller than those obtained when only enforcement is strengthened, with the IQR going from -70 to -55%.[14]

The bottom-left plot of Figure A.3 sums into the relationship between the dif-in-dif estimates of $exp(\alpha_2) - 1$ obtained when only enforcement increases (x-axis) and when both enforcement and flexibility increase (y-axis), using the same realizations of q_{ijt}. 98% of points lie below the dotted 45°

[14]This is the case because flexibility increases the quantity bought through Cenabast more for late payers, increasing average expected late payment when prompt payment enforcement is low (because late payers pay their own purchases quicker than Cenbast purchases when enforcement is low) while decreasing it when prompt payment enforcement is high (because late payers pay their own purchases later than Cenbast purchases when enforcement is high).

line, that is, point estimates when both changes happen underestimates the point estimates that would have been obtained had only enforcement been increased. However, the bias is small, only -1.0 percentage points on average.

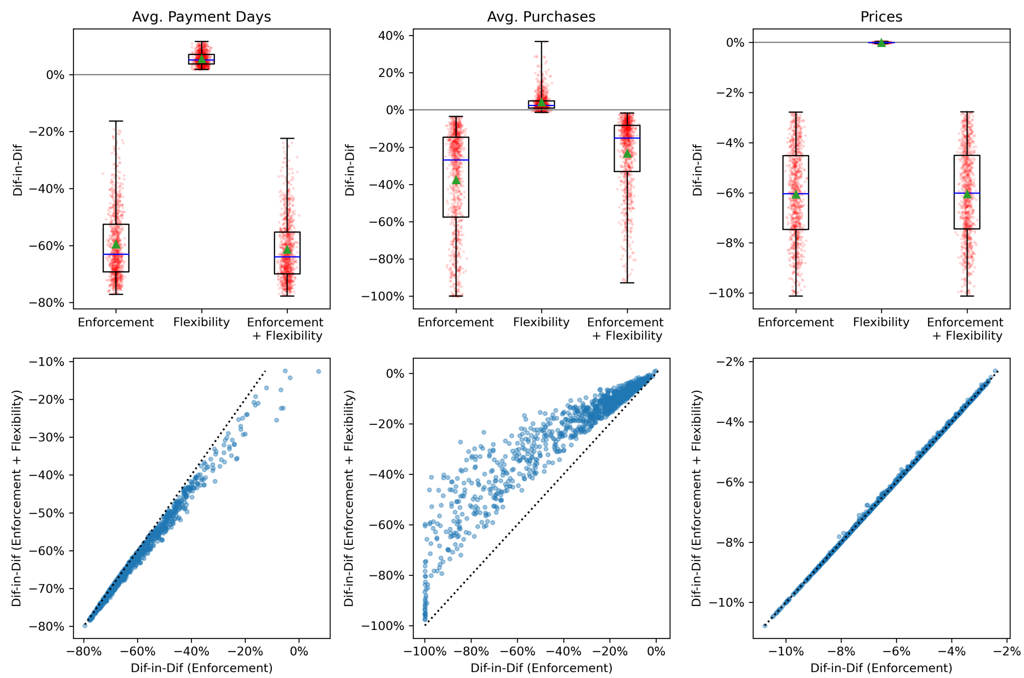

Figure A.3: Comparative statics for medium value of parameters (panel a) and summary statistics of comparative statics across 1,000 scenarios (panel b)

The top-middle plot of Figure A.3 shows box plots with the distribution of $exp(\beta_2) - 1$ when the treatment is enforcement, flexibility, or enforcement and flexibility. These estimates represent the estimated percentage change in hospitals' purchases through Cenabast when moving from zero to one in exposure to stronger prompt payment enforcement. Point estimates are negative across simulations when only prompt payment enforcement changes. The range is quite large, with the IQR going from -58 to -14%. The median and average effects are -27 and -38%. When only demand flexibility increases, the dif-in-dif estimates are positive in most cases and concentrated in small values. The IQR goes from 1 to 5%. When both prompt payment enforcement and demand flexibility increase, the estimates remain negative but closer to zero, with the IQR going from -33 to -8%. The median and the average are -15 and -23%.

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The bottom-middle plot of Figure A.3 sums into the relationship between the dif-in-dif estimates of $exp(\beta_2) - 1$ obtained when only enforcement increases (x-axis) and when both enforcement and flexibility increase (y-axis), using the same realizations of q_{ijt}. All points lie over the dotted 45° line, that is, point estimates when both changes happen overestimate the point estimates that would have been obtained had only enforcement been increased. The bias is quite substantial, 14 percentage points on average.

The top-right plot of Figure A.3 shows box plots with the distribution of $exp(\gamma_2) - 1$ when the treatment is enforcement, flexibility, or enforcement and flexibility. These estimates represent the estimated percentage change in drugs' prices when moving from zero to one in exposure to stronger prompt payment enforcement. Point estimates are negative, with the IQR going from -7.5 to -4.5%. The median and average effects are -6 and -6.1%. When only demand flexibility increases, the dif-in-dif estimates are extremely small in absolute value and tightly clustered around zero, with the IQR going from -0.01 to 0.008%. When both prompt payment enforcement and demand flexibility increase, estimates are almost identical to those obtained when only enforcement is strengthened. The bottom-right plot of Figure A.3 confirms this is the case, with points representing pairs of both estimates tightly aligned along the dotted 45° line. The difference between both point estimates is only 0.02 percentage points on average.