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

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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 from a difference-in-differences estimation indicate that hospitals with greater exposure to the reform, measured by their larger share of late bill payments, reduced their payment delays after 2013 compared to less-exposed hospitals, without compromising healthcare quality. The resulting decrease in the average financial cost of FAs led to lower prices, highlighting the importance of prompt payment enforcement for realizing savings through FAs.

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

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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 achieving universal healthcare coverage by 2030 (Sustainable Development Goal 3.8). 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 et al., 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 dispatches to hospitals with outstanding bills until their balances were cleared. Hospitals that paid a larger share of their invoices late before the procedure was announced in 2013 were more exposed, providing an opportunity to estimate the impacts of stepping up prompt payment enforcement. Three impacts are hypothesized based on simulations from a dynamic model of competitive FA auctions, involving hospitals with differing costs of paying promptly that can choose how much to procure through FAs. 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 only slightly compared to less-exposed hospitals, as hospitals' costs associated with paying promptly are probably small relative to the overall savings from purchasing drugs through FAs. Lastly, prices are expected to exhibit a more pronounced decline for drugs purchased in larger quantities by more exposed hospitals, as their greater reduction in payment delays leads to larger reductions in financial costs for firms supplying these drugs, thereby lowering equilibrium prices in competitive auctions.

Exposure to prompt payment enforcement is measured as the fraction of invoices that were paid late before 2013. Difference-in-differences (DiD) estimators show that doubling exposure to prompt payment enforcement reduces payment days by nearly 10% ($p<5\%$) after 2013, while having a negligible and non-significant impact of -0.2% on FA demand.

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 DiD specification and the weighted average of late payments among a drug's buyers as a measure of treatment intensity, the analysis suggests that doubling a drug's exposure to prompt payment enforcement reduces its price by 21% after 2013, although the estimate is not statistically significant at conventional levels.

The empirical section concludes with an analysis of the potential negative impacts that prompt payment enforcement could have had on hospitals' healthcare. No evidence of changes in the total number of admissions, length of stay, or deceased discharges is found. In addition, dispatch suspensions are rarely triggered and, when applied, reduce hospitals' supply from the FA only slightly, as hospitals can still procure the drug from other suppliers in the FA. Overall, the results suggest that the prompt payment enforcement procedure implemented in Chile was able to significantly reduce hospitals' payment delays and FA prices without compromising drug supply or healthcare quality.

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.[1] In contrast to Akerlof (1970)'s lemons, adverse selection does not emerge from information asymmetries but from rules that preclude firms from charging agencies differentially 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 differentially 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

[1]Heterogeneity also follows from variables that fall outside the control of buyers, such as their location and the markets they procure from. In the case of Chile, Allende et al. (2024) show that market structure explains up to three times the variation attributable to the residual characteristics of buyers in the case of pharmaceutical product prices.

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 remainder of the paper proceeds as follows: Section 2 provides an introduction to the institutional context. In Section 3, the conceptual framework is presented along with the hypotheses. Section 4 outlines the data and the empirical strategy employed. The results are presented in Section 5, followed by concluding remarks in Section 6. Additional details and supplementary results are provided in the Appendix.

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

The Chilean public health system is organized in 29 territorially-defined Health Services. Most hospitals are managed by their Health Service, except *Establecimientos Autogestionados en Red* (EAR). These 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. In contrast, non-EAR hospitals are smaller, carry out more straightforward medical procedures, and lack independent legal personality and patrimony. Nevertheless, they are responsible for implementing the procurement strategies set by Health Services and paying for their procurement.

Hospitals are funded through two mechanisms. Firstly, the Public Health Insurance pays hospitals for the comprehensive resolution of medical conditions that are part of a predetermined value set. Secondly, they receive transfers defined each year in the public budget. On average, about 40% of hospitals' income comes from the first mechanism, although there is considerable variation between hospitals and years.

Hospitals are prohibited from taking loans when their expenditures exceed their income and are required to prioritize personnel payments over procurement. Consequently, hospitals periodically accumulate debt with their suppliers when spending surpasses their income. They manage these debts by extending payment days and paying overdue bills as new resources become available, cycling the debt until expenditures and income reach equilibrium. Hospitals' systematic overspending has been attributed to several factors, including the underestimation of costs during budget setting and the existence of recurrent partial bailouts. While these bailouts are necessary to avoid disruptions in public health services, they may erode hospital managers' incentives to improve the efficiency of procuring, using, and paying for medical inputs (Ahumada et al., 2016). These extraordinary funds are allocated annually by the Budgetary Office, with the Health Ministry determining their distribution among Health Services. The main criterion used to distribute these additional resources is the Debt Criticality Index, calculated as the standing debt divided by one-twelfth of the budget for goods and services. Once the additional resources are disbursed to Health Services, they determine how to allocate the funds among their hospitals.

FAs hold the potential for significantly increase hospitals' procurement efficiency. Instead of procuring drugs independently, hospitals can procure them through Cenabast, a public organization that leverages the share size of hospitals' demand to obtain lower prices. 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.[2] Cenabast retained the task of estimating aggregate demand, conducting auctions, and

[2]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.

selecting winners. While 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, it was not until 2014 that Cenabast introduced a mechanism to enforce prompt payment. The failure to incorporate such a mechanism may have reduced hospitals' incentives to invest in improving their payment procedures and decreased demand from prompt payers, potentially increasing the financial cost of serving FAs and thus reducing the realized savings that FAs are expected to deliver.

The mechanism to enforce prompt payment consisted in allowing firms to suspend dispatches to hospitals with outstanding bills, only for the drugs that had outstanding bills and until balances were cleared. To suspend dispatches to a delinquent hospital for a drug, a firm requires authorization from Cenabast, which verifies that the client has an overdue bill on that drug for over a defined period. A bill was considered overdue after 45 days from the reception of the invoice for most hospitals, with an additional 15 days for EAR hospitals. The suspension was approved if 45 days had passed since the bill was due, with an additional 15 days for EAR hospitals.

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 threat. 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 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 a bill had been overdue over the stipulated limit). In addition, the punishment itself was costly but manageable, restricted to a specific product supplied by a specific firm.

3. Conceptual framework and hypotheses

3.1. Conceptual framework

This section presents the results from a formal model of hospitals' procurement when FAs are available, with the goal of deriving testable hypotheses on the impacts of prompt payment enforcement. Only the central elements of the model are presented here to focus on its predictions. A detailed exposition of the model is presented in Appendix A.

The model considers hospitals that minimize the expected procuring cost of meeting stochastically-determined needs for a set of drugs. For each drug, hospitals must decide the quantity they will procure through a FA or on their own. While FAs are cheaper, hospitals must decide how much to procure before their needs are realized, thus risking accumulating inventories. In contrast, while their own purchases are more expensive, they allow hospitals to save on inventory costs by exactly meeting their needs.

In addition to the quantity procured through FAs, hospitals must decide how much to invest in two prompt payment technologies per drug, one for the FA and another for their own purchases. The technologies reduce the average payment time, thus making late payments less likely. Even though the cost of investing is the same across both technologies, hospitals' perceived benefits differ between them. For their own purchases, hospitals internalize that firms charge the expected cost of payment time. Thus, lower payment times translate to lower prices. For FA purchases, hospitals take FA prices as given but internalize that paying late can be costly with a positive probability. For example, in the empirical application of this paper, these costs reflect the inconvenience of having future dispatches suspended due to late payments. The expected cost of paying FA purchases late is the key parameter of interest, prompt payment enforcement.

Hospitals differ across two dimensions: the cost of investing in prompt payment technologies and the importance of different drugs in their needs. Given this, the model is closed by assuming free entry of firms into competitive auctions. Importantly, firms anticipate the expected financial cost of serving FAs when setting their bids for FA auctions, considering the composition of hospitals that will buy from each FA and their payment times. Under sensible specifications for prompt payment technologies and the stochastic process that determines drugs' needs, there exists a closed-form solution for hospitals' problems given FA prices. A unique equilibrium is guaranteed to exist, which can be found numerically.

Figure 1 shows the results from a numerical simulation, where prompt payment enforcement is stepped up in period zero. The results illustrate the evolution of expected payment days and demand from FAs across hospitals with different exposure to prompt payment enforcement (top and middle plots), along with the evolution of FAs prices across drugs with different exposure to prompt payment enforcement (bottom plot).

The top plot displays the evolution of expected payment days for the hospital with the lowest, median, and highest exposure to prompt payment

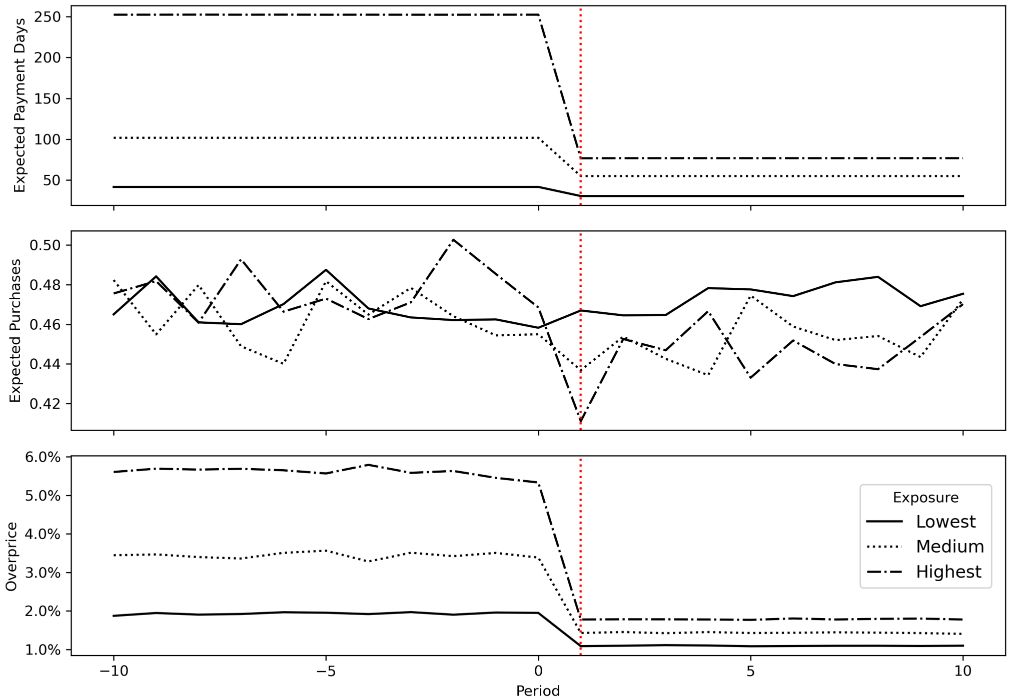


Figure 1: Evolution of expected payment days (top), expected purchases to FA (middle), and FAs' prices (percentage over marginal cost), before and after the tightening of prompt payment enforcement (red vertical dotted line), for hospital (top and middle) or drug (bottom) with lowest (black solid line), median (black dotted line) and highest (black dashed-dotted line) exposure to prompt payment enforcement.

enforcement (solid, dotted, and dashed lines), measured as the fraction of bills that were paid late before period zero. The model predicts a larger decline in expected payment days for hospitals with greater exposure to prompt payment enforcement, as the increase in enforcement raises the marginal benefit of reducing payment delays for all hospitals but has a stronger effect on those with a higher share of late-paid bills subject to enforcement.

The middle plot of Figure 1 shows, for the same three hospitals, the evolution of their expected FAs' purchases. The introduction of prompt payment is predicted to have a larger impact on hospitals that are more exposed, especially in the short run as they accommodate towards lower desired levels of inventories. This is because enforcement increases the marginal cost of purchasing through FAs for all hospitals but affects late payers more significantly, as prompt payment constitutes a larger share of their overall costs. However, note that the impact on demand is expected to be small across the board, as the costs associated with investments in prompt payment technologies are small compared to the difference in marginal cost between FAs and own purchases. In addition, the stochastic nature of needs introduces random shocks to hospitals' demand from FAs, challenging the detection of small impacts.

The bottom plot shows the evolution of prices (percentage over marginal costs) for the drugs with the lowest, median, and highest exposure to prompt payment enforcement. Exposure is measured as the average payment time across the pool of each drug's buyers, weighted by their demand for that drug. Consequently, drugs with higher exposure are those more intensively demanded by late payers. Because late payers reduce their payment delays more significantly, the financial cost of serving highly exposed drugs decreases more substantially. Under the assumption of competitive auctions, this results in greater price reductions for these drugs.

3.2. Hypotheses

The previous results on hospitals' average payment days, FA demand, and drug prices support the following hypotheses about the consequences of the 2013 announcement of prompt payment enforcement in Chile's hospital FAs:

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

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

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

The model suggests sizable quantitative impacts for Hypotheses 1 and 3, while for Hypothesis 2, it predicts small differential effects of prompt payment enforcement between prompt and late payers, which may be difficult to detect empirically.

4. Data and empirical strategy

4.1. Data

The main analyses of this paper use data on the demand from Cenabast's FAs, hospitals' payment behavior and budgetary execution, and FAs auctions. This section explains how these data were obtained and processed.

Hospitals' Purchases From Cenabast: Data on purchased drugs from Cenebast's FAs between January 2010 and December 2015 were provided by Cenebast. Drugs are identified by their unique ID that identifies a specific combination of active components, concentration, and formulation (e.g., acetaminophen, 150mg/100ml, oral drops). 175 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 1,790 different drugs. The data is collapsed at the hospital-year level to obtain annual real purchases from Cenabast for each hospital. Drugs' prices are kept constant to calculate real purchases, using the average inflation-adjusted price of each drug before the announcement of prompt payment enforcement.

Late Payment: Invoice-level data on public agencies' payments between January 2010 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 paid by public hospitals' is processed to construct a novel database that describes annual payment behavior for 175 hospitals between 2010 and 2014. For each year, the database shows the average days it took each hospital to pay the invoices received during the year and paid within a year, along with the fraction of invoices that were paid late and paid within three years before the announcement of the prompt payment enforcement mechanism on 2013 (over 45 days for non-EAR hospitals and 60 days for EAR hospitals).[3] This latter statistic is conceptualized as hospitals' exposure to prompt payment enforcement.

Cenabast's Auctions: Data on Cenabast's auctions between January 2010 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. 4,741 out of the universe of 5,180 auctions include an identifier of the drug in the auction's description, the same used to identify drugs in the database with purchases from Cenabast.

[3]Bills paid in more than a year are not considered for the yearly average payment delay calculation because late payers have a larger fraction of bills payed after 2015, which are not observed in the data. Hence, an unconstrained average would introduce a larger bias for late payers, with the gap growing for later years.

Out of the 1,132 drugs included in these auctions, 489 are selected for the analysis because they are purchased by one or more of the 175 selected hospitals, have been auctioned in two or more years in the sample period, and are consistently defined throughout the sample period.[4] The auctions associated with these products had 5,580 bids placed by 191 firms. The data are collapsed at the drug-year level, calculating the price as the weighted average of the winning bids, using awarded quantities as weights.

Exposure to prompt payment enforcement for drug d, Exp_d, is defined as the average exposure of hospitals that buy drug d weighted by their demands before the announcement of prompt payment enforcement:

$$Exp_d = \sum_{i=0}^{N} \frac{x_{id}}{X_d} Exp_i, \tag{1}$$

where Exp_i is exposure of hospital i, x_{id} is the amount of drug d bought by hospital i through Cenabast before the announcement, and X_d is the amount of drug d bought by all hospitals through Cenabast before the announcement.

Debt Criticality Index (DCI): For each Health Service, the DCI is constructed using public data published by the Chilean Supreme Audit Institution (Contraloría General de la República, 2022). The index is defined as the standing debt from current goods and services in year $t-1$ (the difference between accrued and paid expenditures, including debt rollover from $t-2$) divided by one-twelfth of the budget for current goods and services in year t. Thus, the index measures Health Services' procurement debt burden in terms of their monthly budget. The analysis focuses on the value of the index as of the start of 2013, right before the announcement of the prompt payment enforcement mechanism. Data on the total budget for current expenditures in 2013, split into variable and fixed components, are also obtained for descriptive purposes.

Hospitals' Discharges (2008-2015): Data on hospital discharges were provided by the Department of Health Statistics and Information (DEIS) from the Ministry of Health. These data are used for describing prompt and late payers in this section and for the supplementary analyses of the

[4]The internal codes used by Cenabast to identify drugs in the auction dataset changed in 2011. While Cenabast provided a file linking both codes, some drugs, as specified by their 2011 codes, were lumped together into a single code in 2010. Those drugs are excluded.

Appendix. Six out of the 175 hospitals in the sample are not found in these data.[5] Only data from 2008 is used because the Chiloé Health Service, which oversees hospitals that are part of the sample, was created at the end of 2007. Each row represents a discharge and indicates the hospital, date of admission, sex, age group, length of stay, diagnosis (International Disease Classification Code), and discharge status (alive or deceased). The data is aggregated to the hospital–year-of-admission level, creating three variables that roughly capture the quantity and quality of health care: total admissions, the average length of stay, and total deceased discharges.

4.2. Differences between prompt and late payers

Table 1 shows how prompt and late payers, defined by their exposure to prompt payment enforcement above or below the median, differ across several variables at the baseline—2012.[6] Panel a focuses on variables that characterize the Health Services hospitals belong to. Interestingly, prompt and late payers do not differ in whether their Health Services are located in the metropolitan region of Santiago, the number of admissions per hospital, their total budget, or the fraction of the budget that is variable—linked to the volume of medical conditions resolved. Late payers belong to Health Services that have fewer hospitals, although the difference is not striking—7.42 vs. 8.49—but is significant at the 10% level. In contrast, they do significantly differ in terms of their Health Services' DCI, with an average DCI of 1.38 for late payers compared to 0.85 for prompt payers ($p < 1\%$).

Panel b describes the characteristics of hospitals. Late payers are much more likely to have EAR status, with 41% being EAR compared to 13% of prompt payers ($p < 1\%$). As expected from the larger size of EAR hospitals, this difference correlates with a significant disparity in hospital size based on the number of admissions: 9.7 thousand for late payers compared to 2.5

[5] In the medical discharge data, hospitals are identified only by an internal code of the Ministry of Health, which changed in 2014. Therefore, the hospitals' discharge data were linked across years using a file published by DEIS that contains both the old and new codes along with hospital names (DAIS, 2019), and to the procurement and late payment data using hospital names. Three hospitals were excluded because they are not listed in the DEIS file, and three more hospitals were excluded because, although listed in the file, the codes did not match any in the discharge data.

[6] Variables derived from budgetary data (budget per hospital, fraction of variable budget, and DCI) are based on the 2013 budget, which was approved in 2012.

Table 1: Characteristics of prompt and late payers

Variable	N	Prompt payers	Late payers	P-value
	(1)	(2)	(3)	(4)
Panel a: Characteristics of Hospitals' Health Services:				
Santiago region	175	0.102	0.149	0.35
Number of hospitals	175	8.49	7.52	0.09
Budget per hospital (M USD)	175	1.346	1.247	0.26
Frac. variable budget	175	0.367	0.362	0.70
Debt criticality index	175	0.854	1.380	0.00
Admissions per hospital	169	5,981	6,222	0.68
Panel b: Characteristics of Hospitals:				
EAR status	175	0.125	0.414	0.00
Total admissions	169	2,528	9,694	0.00
Average length of stay	169	6.42	7.21	0.62
Average frac. deceased	169	0.0259	0.0249	0.63
Average payment days	175	19.4	52.9	0.00
FA buys (K USD)	175	186	810	0.00
FA buys per admission (USD)	169	133	95	0.01

For each variable in the rows, column 1 shows the number of hospitals for which the variable is not missing. Columns 2 and 3 display the averages for prompt payers and late payers, with the threshold defined by the median of the fraction of invoices paid late before 2013 (exposure to prompt payment enforcement). Column 3 shows the p-value of the difference between the averages of both groups. Panel a displays variables that characterize hospitals' Health Services, while panel b variables that characterize hospitals. 'Frac. variable budget' denotes the portion of the budget dependent on the resolution of medical conditions and 'Average frac. deceased' refers to the average fraction of deceased discharges. Monetary values have been converted to 2023 USD. All variables are from 2012 (variables derived from budgetary data—'Budget per hospital', 'Frac. variable budget', and 'Debt criticality index'—are based on the 2013 budget, which was approved in 2012).

thousand for prompt payers ($p < 1\%$).[7] However, prompt and late payers do not differ significantly in the average length of patients' stay or the fraction of deceased discharges. Late payers take an average of 53 days to pay upon receiving an invoice, compared to 19 days for prompt payers. Thus, the higher

[7] Average admissions for EAR and non-EAR hospitals are 13.5 and 2.4 thousand.

fraction of late payments reflects a shift in the entire distribution rather than just at the margin defining late payment thresholds. Finally, while the total value of purchases from Cenabast FAs is higher for late payers, this difference is due to their larger size. Indeed, expenditure in Cenabast FAs per admission is lower for late payers, \$95 vs. \$133 ($p < 1\%$).[8]

Figure C.7 delves deeper into the relationship between late payment on one hand, and EAR status and DCI on the other. The correlation is stronger for EAR status, inducing a strong positive relationship between drugs' exposure to prompt payment enforcement and the fraction of drugs' purchases demanded by EAR hospitals. While the correlation between prompt payment enforcement and DCI is also positive for hospitals, it does not translate into a positive correlation between both variables as defined for drugs.

4.3. Empirical strategy

This section presents the empirical strategy employed to test the hypotheses. Given that the hypotheses are stated in terms of the relative impact of stepping up prompt payment enforcement on hospitals or drugs, a Two-Way Fixed Effects (TWFE) specification with a continuum treatment variable follows naturally:

$$y_{it} = \alpha_i + \alpha_t + \sum_{k \neq -1} \beta_k \mathbb{1}(t - 2013 = k) Exp_i + \mathbf{X_{it}} \mathbf{\Theta} + \varepsilon_{it}, \qquad (2)$$

where y_{it} is the natural logarithm of an outcome of interest for unit i (hospital or drug) in year t; Exp_i is the natural logarithm of exposure to prompt payment enforcement for unit i, defined as the fraction of bills paid late for a hospital or a drug before the mechanism was announced in 2013; X_{it} include additional controls that vary within units and years, discussed at the end of this section; α_i and α_t are units and years fixed effects; and ε_{it} is a zero-mean disturbance. Units fixed effects will control for the differences between prompt and late payers reported in Table 1.

[8] While the model predicts that late payers will experience a larger reduction in purchases from FAs after prompt payment enforcement is stepped up (Hypothesis 2), it does not predict a higher level of purchases from FAs for late payers when prompt payment enforcement is low. This is because the relative price difference between direct purchases to firms made by late and prompt payers is small compared to the price difference between Cenabast and hospitals' own purchases.

Three dependent variables are used, one for each hypothesis: the natural logarithm of average payment days for the first hypothesis, the natural logarithm of purchases from Cenabast for the second, and the natural logarithm of average drugs prices for the third. The unit of analysis is a hospital for the first two dependent variables and a drug for the third. The parameters of interest are the β_k. For $k \geq 0$, they capture the elasticity of exposure to prompt payment enforcement on the outcome of interest k periods after the announcement relative to the year before the announcement, 2012—the excluded year in equation 2. For $k < -1$, β_k provides estimates of differential pre-trends between units with different levels of exposure to the reform. These estimators are used to assess the plausibility of parallel contrafactual trends in the absence of the treatment after t^*.

In addition to reporting dynamic DiD estimates, average treatment effects for two post-announcement periods are obtained by estimating:

$$y_{it} = \delta_i + \delta_t + \gamma_1 Ann_t Exp_i + \gamma_2 Imp_t Exp_i + \mathbf{X_{it}} \mathbf{\Lambda} + \nu_{it}, \tag{3}$$

where Ann_t is an indicator function for the periods when the mechanism to enforce prompt payment had been announced but was not yet implemented (2013), and Imp_t is an indicator for the periods when the mechanism was in place (since 2014). The rest of the equation is defined analogously to equation 2.

The specifications that test the first two hypotheses are run at the hospital-year level. In contrast, the specification that tests the third hypothesis is run at the drug-year level. Standard errors are clustered at the hospital or drug level for inference.

Threats to identification: Identification relies 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. In addition to the three outcome variables (Figure 2), the paper tests the validity of the identification strategy on three variables for which there is a longer pre-treatment period available (since 2008): total admissions, the average length of stay, and the number of deceased discharges (Figure C.8); and checks the robustness of the results to violations of the parallel trends assumption using Rambachan and Roth (2023)'s partially identified Relative Magnitude Estimator (Figure C.9).

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, the effects of flexibility are expected 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 the estimators. In the case of purchases from Cenabast, 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 could also bias the results, as EAR hospitals are, on average, more exposed to prompt payment enforcement (see Table 1 and Figure C.7). For this reason, all specifications include the interaction between an EAR dummy and year dummies in X_{it}, thus allowing for differential trends between EAR and non-EAR hospitals. EAR-status offers the additional advantage of having a strong correlation with total admissions, which is not available for all hospitals. Indeed, EAR status explains 53% of the variation in total admissions.

Finally, Debt Criticality could also bias the results because more exposed hospitals belong to Health Services with higher levels of the Debt Criticality Index (DCI) as of the start of 2013 (see Table 1 and Figure C.7). These Health Services could have obtained additional resources to reduce their debt, which could introduce a spurious correlation between exposure and payment delays with an ex-ante ambiguous sign. On the one hand, the additional resources were meant to help serve the debt, potentially reducing payment days. On the other hand, higher accumulated debt hampers hospitals' capacity to promptly pay incoming invoices. For this reason, all specifications includes a dummy that equals one for hospitals that had a DCI above the median in 2013 interacted with year dummies in X_{it}, thus allowing for differential trends between hospitals below and above the median.

By incorporating interactions of EAR and DCI dummies with year fixed effects, our estimations leverage variations in treatment intensity within EAR and non-EAR hospitals, as well as within hospitals with DCI below and above the median. This approach ensures robustness against potential differential trends among these groups of hospitals and enhances statistical power, given the relevance of EAR and DCI as determinants of the outcome variables.[9]

5. Results

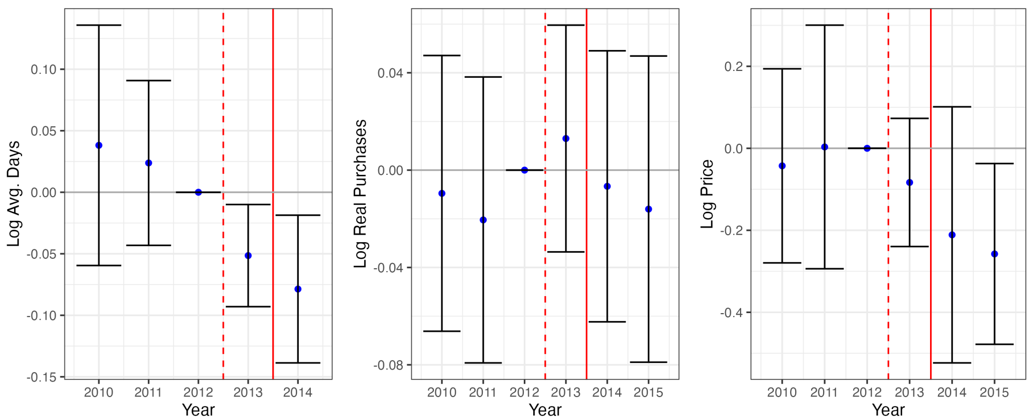
5.1. Evidence from DiD dynamic estimates

Figure 2 displays the dynamic DiD estimates for payment days (panel 2a), real purchases from Cenabast (panel 2b) and Cenabast's prices (panel 2c). The timing of the announcement of the mechanism to enforce prompt payment is depicted as a red vertical dashed line, and the timing of its implementation as a red vertical solid line. The joint null hypothesis of no differential pre-trends cannot be rejected at the 10% level for any of the plots, providing support to the validity of the parallel trends assumption and that the prompt payment enforcement procedure was not anticipated before its announcement.

Overall, the results presented in Figure 2 support the hypotheses of this study. Panel 2a shows that hospitals started reducing their payment days the same year the policy was announced, with a doubling of exposure to prompt payment enforcement reducing average payment days by 5.1% ($p < 5\%$). The reduction is likely to have followed before the implementation of prompt payment enforcement because it takes time to reduce payment days, both due to the required financial planning and because unpaid bills accumulate. Hence, if hospitals wanted to reduce their exposure to the suspensions of dispatches in the future, they needed to start working on improving their payment procedures as soon as the policy was announced. By the first year the policy was implemented, a doubling of exposure to prompt payment enforcement is estimated to have reduced average payment days by 7.9% ($p < 5\%$). The joint test of zero impacts following the announcement is rejected at the 5% level.

Panel 2b shows that the analysis detects no impact of prompt payment enforcement on the quantity bought from Cenabast, although the point estimates after the policy was implemented are negative, as expected. The specification was expected to be underpowered for this hypothesis, as the theoretical model suggests the effects are small because investments in prompt payment are small compared to the price difference between Cenabast and

[9] Hypothesis 3 uses the fraction bought by EAR hospitals instead of a EAR dummy, and the fraction bought by hospitals with DCI above the median instead of a DCI dummy.



(a) (b) (c)

Figure 2: Dynamic DiD estimates of the impact of prompt payment enforcement on payment days (a), quantities (b), and prices (c). The dashed red line represents the announcement of the mechanism stepping up prompt payment enforcement and the red solid line its implementation. Blue dots represent TWFE estimates and black vertical lines 90% confidence intervals (standard errors are clustered at the hospital level in panels a and b, and at the drug level in panel c).

hospitals' own purchases. In addition, the increase in flexibility is expected to introduce a positive bias to this estimator, further hampering the possibility of detecting a negative effect. The joint tests of zero impacts following the announcement and implementation cannot be rejected at conventional significance levels.

Consistent with a reduction in the financial burden imposed by late payment on firms, panel 2c suggests that prices of drugs purchased in larger quantities by more exposed hospitals experienced a larger reduction. The reduction in prices has become more pronounced as the policy has settled, suggesting that firms have waited to observe a reduction in payment days to update their expected financial cost of serving FAs. By 2015, a doubling of exposure to prompt payment enforcement is estimated to reduce prices by 25.8% ($p < 10\%$). However, the joint tests of zero impacts following the announcement and implementation cannot be rejected at conventional significance levels.

5.2. Average treatment effects

Table 2 displays the treatment effects on average payment days (column 1), real purchases from Cenabast (column 2), and drug prices (column 3). Treatment effects are calculated for two periods: between the announcement and the implementation of the mechanism to enforce prompt payment enforcement (Ann, 2013), and after the implementation (Imp, since 2014). Column 1 shows that a doubling of exposure to prompt payment enforcement is estimated to reduce payment days by 7.2% in the year of the announcement and by 9.9% after implementation, both significant at the 5% level. In contrast, column 2 shows that the point estimates of the impact of prompt payment enforcement on real purchases from Cenabast are very small and inconsistent in their signs, with a small, non-significant point estimate of a 2.3% increase in real purchases in the year of the announcement for a doubling of exposure to prompt payment enforcement, and a negligible, non-significant reduction of 0.2% after the implementation. Finally, column 3 shows that while no impacts are detected for prices at conventional levels, the point estimates are negative and large in absolute value—a 21.4% reduction for a doubling of exposure to prompt payment enforcement after the implementation—suggesting that the reduction in payment days found in column 1 translated to a reduction in drug prices.

The complete results, including the interaction between Ann and Imp with EAR status and the DCI, are included in Table C.3. The results confirm that the inclusion of these variables is important, as EAR hospitals experienced a significant increase in payment days after implementation, whereas drugs bought more intensively by EAR hospitals saw a reduction in their prices after implementation. Hospitals with a higher DCI experienced a larger increase in their payment days in the year prompt payment enforcement was announced (2013), suggesting that the potential extra resources received to reduce their debt were not enough given the burden of their accumulated procurement debt.

The results closely align with the predictions of the theoretical model, providing support for the three hypotheses of this study. On the one hand, prompt payment enforcement induces larger reductions in payment days for late payers, thereby lowering the financial cost of serving drugs heavily demanded by them and, consequently, reducing these drugs' prices. On the other hand, the impacts of prompt payment enforcement on late payers' demand are negligible, as the costs associated with prompt payment enforcement represent only a small share of the savings realized through FAs.

Table 2: Average treatment effects after announcement and implementation of prompt payment enforcement mechanism

Dep. var:	log(*Avg. Days*)	log(*Purchases*)	log(*Prices*)
	(1)	(2)	(3)
$Exp \times Ann$	-0.072**	0.023	-0.072
	(0.035)	(0.025)	(0.097)
$Exp \times Imp$	-0.099**	-0.002	-0.214
	(0.042)	(0.082)	(0.152)
Observations	871	1,041	1,824

Observation level is hospital-year in columns 1 and 2, and drug-year in column 3. Standard errors clustered at the hospital (columns 1 and 2) and drug (column 3) in parenthesis below point estimates. *Exp*, *Ann*, and *Imp* stand for Exposure, Announcement, and Implementation. All specifications include interactions of *Ann* and *Imp* with EAR-status and the 2013 Debt Criticality Index. Stars next to point estimates denote statistical significance: * $p< 0.1$, ** $p< 0.05$, *** $p< 0.05$.

However, caution is warranted when interpreting specific point estimates, particularly regarding the reduction in prices, due to constraints in statistical power.

5.3. Robustness

While we cannot reject the null hypothesis of no pre-trends for the three dependent variables of interest, this does not confirm that pre-trends consistent with the estimated confidence intervals do not bias the results (Roth, 2022).

The paper provides two additional exercises to further support the validity of the parallel trends assumption. First, Figure C.8 shows the result of dynamic DiD estimates on three variables derived from information on hospitals' discharges between 2008 and 2015: the natural logarithm of total admissions, the natural logarithm of the average length of stay; and the natural logarithm of the number of deceased discharges. No evidence of pretrends is found for these variables between 2008 and 2011, with only one out of twelve (<10%) pre-2012 estimates significantly different from zero at the 10% level. The null hypothesis of no pretrends cannot be rejected at the 10% level for any of the variables.

Second, the robustness of the results to violations of the parallel trends assumption is assessed using Rambachan and Roth (2023)'s partially identified Relative Magnitude estimator. The estimator allows for the parallel trends assumption in the post treatment period to be violated by a fraction of the maximum deviation from the parallel trends assumption found in the pre-treatment period, obtaining partially identified bands that contain the true parameter of interest with 90% confidence, given the maximum assumed violation. The results, presented in Figure C.9, show that the significant reductions in payment days reported in column 1 of Table 2 for the announcement and implementation of prompt payment enforcement are robust to violations of the parallel trends assumption of up to 30% and 25% of the maximum deviation found in the pre-treatment period, respectively.

Taken together, these exercises suggest that the parallel trends assumption is plausible, given the absence of evidence showing violations in the pre-treatment period across both the main dependent variables of this study and three additional variables. However, low statistical power renders the results vulnerable to relatively small violations of the parallel trends assumption.

5.4. Unintended consequences on health care

The previous results provide support for the hypothesis that prompt payment enforcement can improve the financial health of hospitals in the long term by encouraging investment in better management systems that reduce payment days and procurement prices. However, one may be concerned that the disruptions brought by suspending scheduled dispatches upon failure to pay promptly negatively impact the quantity and quality of hospitals' healthcare. Here, it is argued that the prompt payment enforcement mechanism studied in this paper did not have such unintended negative consequences. Suspensions were restricted to the specific firms and products associated with the overdue invoices that triggered them and were only implemented after firms requested authorization from Cenabast to suspend future dispatches. Thus, hospitals' supply of a given drug was unlikely to be jeopardized by a suspension, especially considering that suspensions were lifted as soon as hospitals paid the bill in question.

A first piece of evidence consistent with this argument is the lack of an effect of exposure to prompt payment enforcement on hospital admissions, average length of stay, or death discharges, as shown in Figure C.8. If prompt payment enforcement had reduced hospitals' capacity to admit patients, we would observe a decrease in admissions as hospitals refer patients to other facilities. If prompt payment enforcement had jeopardized hospitals' ability to manage their patients' medical conditions, we would expect changes in patient length of stay—either discharging patients earlier to conserve resources or keeping them longer due to delayed healing from insufficient medication—or an increase in patient mortality. However, we do not observe significant impacts on any of these variables, with small and non-significant point estimates.

Appendix B combines data from monthly purchases from Cenabast between 2019 and 2023 with data on dispatch suspensions requested by firms during the same period to assess the consequences of dispatch suspensions on hospitals' drug supply. First, it is found that requests to suspend dispatches are infrequent: on average, only 1.3% of dispatches associated with 2019 purchase orders have triggered a suspension. Secondly, a staggered DiD estimator, which takes the first approved suspension of a dispatch for a given drug-hospital combination as the event, shows that the effect of suspensions on hospitals' drug supply is limited. The probability of receiving a dispatch drops by less than 20 percentage points after 5 months following a suspension. This limited impact reflects the use of several mechanisms through which hospitals can overcome a suspension, including paying to reinstate dispatches or using alternative suppliers. Appendix B explains the estimation in detail and explores the likely use of these mechanisms.

Taken together, the low percentage of dispatches that lead to future suspensions, the minimal impact of these suspensions on drug supply, and the lack of evidence regarding the impacts of prompt payment enforcement on hospitals' health care services strongly suggest that the application of prompt payment enforcement did not compromise the quantity and quality of health care in Chilean hospitals.

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 stepped up 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 dispatches to hospitals with outstanding bills. Using a difference-in-differences research design and employing the pre-reform fraction of hospitals' late payment as a measure of treatment intensity, the findings demonstrate that hospitals with higher exposure to the reform experienced reductions in payment delays compared to hospitals with lower exposure. Furthermore, the findings suggest that drugs procured in larger quantities by late payers exhibited larger price reductions, in line with firms adjusting prices to the reduction of the average credit risk of FAs as late payers reduced their payment delays.

Remarkably, the results show that prompt payment enforcement was able to deliver savings without compromising hospitals' drug supply and healthcare services. This is likely due to the narrow application of the prompt payment enforcement mechanism, which was rarely employed and restricted dispatch suspensions to the specific product and firm associated with an overdue bill, as signaled by a firm's formal request for suspension. This suggests that even minor costs for paying late may be enough to significantly increase buyers' efforts to pay promptly, who may end up paying these costs infrequently in equilibrium as their payment procedures improve. However, caution should be exercised when extrapolating the results from this study to other contexts where prompt payment enforcement imposes larger costs, as healthcare services may be jeopardized. Exploring the behavioral mechanisms through which minor costs can effectively improve buyers' payment behavior is an interesting area for future research.

The findings from this study gain particular relevance against the backdrop of the reform occurring during a period of historically low interest rates. As interest rates have risen globally, the detrimental effects of inadequate prompt payment enforcement on FAs are expected to become more pronounced. Moreover, 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 another 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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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 from 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 from Cenabast $x^m_{ijt} \in [x_{ijt} - \varepsilon\mu_{ij}, x_{ijt} + \varepsilon\mu_{ij}]$, inventories in $t+1$ are given by

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

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

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

where r is firms' daily discount rate.[10]

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).[11] Hence, they select λ^d_{it} by solving

$$\Omega^*_c = \min_{\lambda^c_{ijt}} \quad \lambda^c_{ijt} a + p^c_{jt} \left(1 + e^{-\lambda^c_{ijt} M} K\right), \tag{A.3}$$

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

[11]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.

where $e^{-\lambda^c_{ijt}M}$ is the probability hospital i pays drug j acquired through Cenabast in period t in more than M days and p^c_{jt} 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 $\Omega^*_c < \Omega^*_d$,[12] hospitals' Bellman Equation for drug j is

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

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 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:

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

[12] If $\Omega^*_c \geq \Omega^*_d$, the problem has a trivial solution at $x(I) = 0$.

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:

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

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.[13]

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.[14] Under these conditions, the expected value of winning a bid with posted price p_{jt}^c for drug j in period t is given

[13] $\gamma \in (0, \kappa)$ can reflect the effect of economies of scale associated to the large volume of Cenabast FAs. 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.

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

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 from 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 $E(x^m)$ is decreasing in p—eventually reaching $E(x^m)=0$ 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 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.3 shows the results for a parametrization where $M=90$, $r=12.5\%$ (annually), $c=0.03$, $\beta=0.925$, $\kappa=1$, and $\gamma=0.3$. 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.[15]

Figure A.3 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 from 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 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, although more attenuated, 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 2.0 to 1.1%, the drugs with the medium and highest exposure experienced reduc-

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

tions from 3.5 and 5.8 to 1.5 and 2.0%.

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).[16] 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-differences (DiD) specifications are run with the simulated data, for each treatment in each 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 takes 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

[16]Parameters are drawn from the following uniform distributions: $r = U(0.05, 0.2)$, $c = U(0.01, 0.05)$, $\beta = U(0.86, 0.99)$, $\gamma = U(0.2, 0.4)$, $K_1 = U(0.3, 0.6)$, $e_1 = U(0.05, 0.15)$.

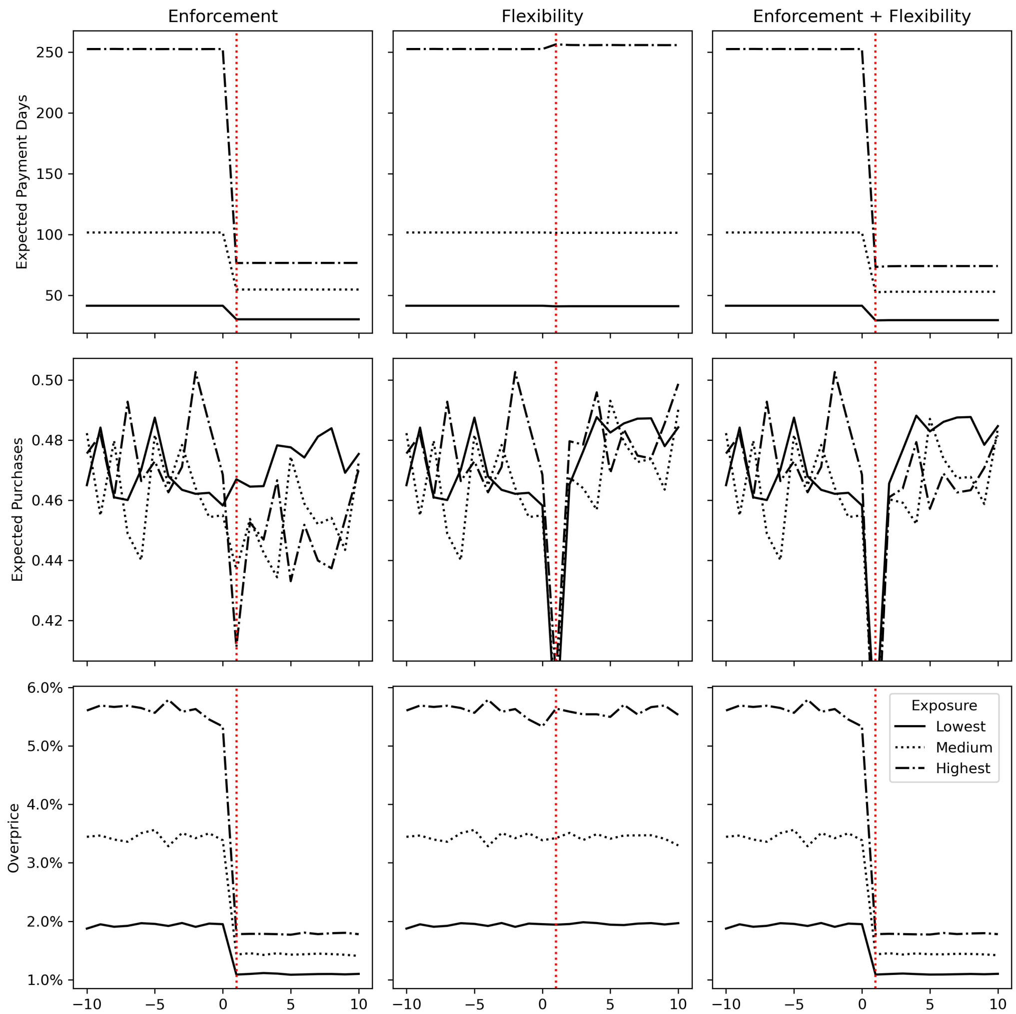


Figure A.3: Evolution of payment days (top row), purchases from Cenabast (middle row), and prices (bottom row) before and after the introduction of prompt payment enforcement (left column), demand flexibility (middle column), and both (right column). Red vertical dotted line indicates period where the implementation of the respective policy change takes effect. Solid, dotted, and dashed black lines represent the hospital (top and middle rows) or drug (bottom row) with the lowest, median, and highest exposure to prompt payment enforcement.

impact of the treatment on hospitals' payment delays, hospitals' demand from Cenabast, and drugs' prices.

The top-left plot of Figure A.4 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 -78 to -69%. The median and average effects are -74 and -73%. When only demand flexibility increases, the DiD estimates are small and positive, with the IQR going from 2.8 to 5.3%. When both prompt payment enforcement and demand flexibility increase, estimates are slightly smaller than those obtained when only enforcement is strengthened.[17]

The bottom-left plot of Figure A.4 sums into the relationship between the DiD 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}. 88% of points lie below the dotted 45° 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 -0.5 percentage points on average.

The top-middle plot of Figure A.4 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 from 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 IQR goes from -17 to -5%, and the median and average effects are -9 and -12%. When only demand flexibility increases, the DiD estimates are positive in most cases and concentrated in small values. The IQR goes from 0 to 1.7%. When both

[17]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 Cenabast purchases when enforcement is high).

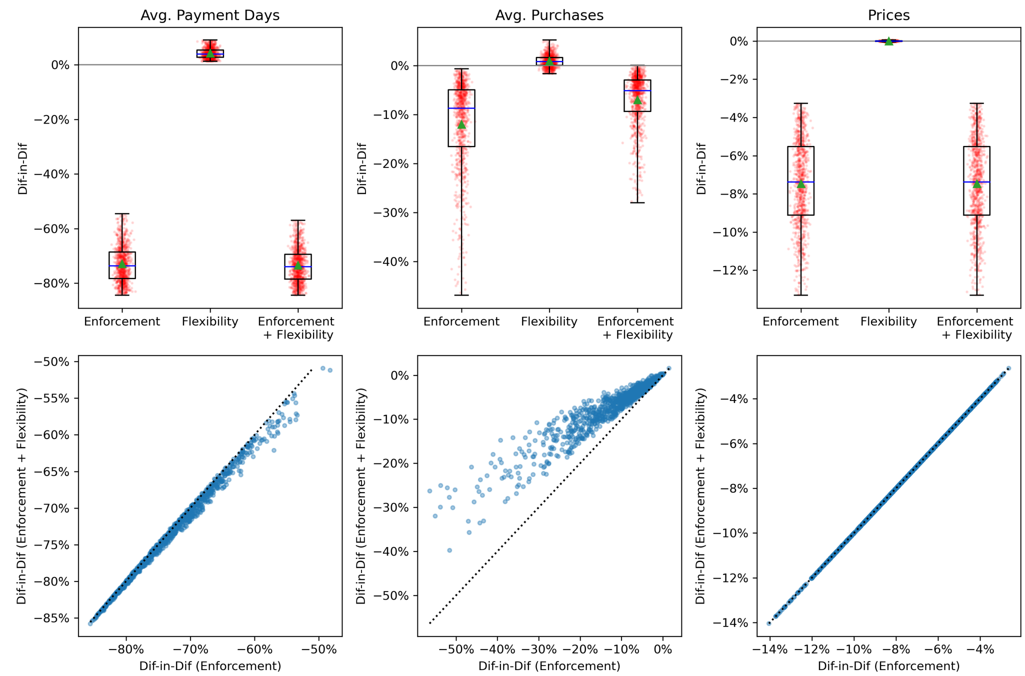


Figure A.4: Comparative statics for medium value of parameters (panel a) and summary statistics of comparative statics across 1,000 scenarios (panel b)

prompt payment enforcement and demand flexibility increase, the estimates remain negative but closer to zero, with the IQR going from –9 to -3%. The median and the average are -5 and -7%.

The bottom-middle plot of Figure A.4 sums into the relationship between the DiD 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, 5 percentage points on average.

The top-right plot of Figure A.4 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 -9 to -5.5%. The median and average effects are -7.4 and -7.5%. When only demand flexibility increases, the DiD estimates are extremely small in absolute value and tightly clustered around zero, with the IQR going from -0.01 to 0.01%. 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.4 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 0.002 percentage points on average.

Appendix B. The impacts of dispatch suspensions

This section estimates the impacts of dispatch suspensions on hospitals' drug supplies by combining data on dispatch suspensions with data on hospitals' purchases from Cenabast.

Appendix B.1. Data

Requests to Suspend Dispatches (2019-2023): These data were provided by Cenabast and contain requests by firms to suspend dispatches. The data specify the firm making the request, the ID of the purchase order linked to the overdue invoice, the tax identification number of the hospital with the overdue bill, the date the request was filed, the status of the request (authorized, regularized, or observed), and the date associated with the status. The data are collapsed at the hospital–month–purchase-order level, creating a dummy variable that equals 1 if a request to suspend a dispatch was filed in a month for dispatches associated with a purchase order.

Hospitals' Purchases From Cenabast (2018-2023): These data, available on the Cenabast website, are structured similarly to the data from purchases through Cenabast between January 2010 and December 2015, covering a different period and containing more detailed information (Central Nacional de Abastecimiento, 2024). Importantly, it includes the ID of the purchase order associated with each monthly dispatch. These IDs are unique identifiers for the generic purchase order that Cenebast creates for auctions' winning bidders in a given drug, thus are repeated multiple times across hospitals and months and are associated to a unique firm. They are associated to a unique drug in over 99% of cases, which allows to merge these data with the data on requests to suspend dispatches. For the purpose of the analysis, the data are aggregated at the hospital–drug–month–purchase-order level.

Although a suspension applies to a specific drug, only 0.1% of purchase orders have more than one associated drug in the hospitals' purchases data. Therefore, those cases are dropped from the sample, and data on hospitals' purchases are linked with data on requests for suspensions using the hospital's tax identifier, the purchase order ID, and the month and year of the suspension request.

Appendix B.2. Frequency of suspensions

First, the analysis describes the likelihood of an invoice triggering a suspension of dispatches in the future. To this end, the analysis focuses on purchase orders associated with hospitals' purchases through Cenabast FAs throughout 2019.[18] For these purchase orders, the total number of suspensions associated with these orders between 2019 and 2023 is calculated for each hospital. To obtain the relevant denominator, i.e., the total number of dispatches that could have triggered these suspensions, dispatches to hospitals associated with the same purchase orders between September 2018 and December 2023 are added up. These are the dispatches that could have triggered a suspension of future dispatches starting in January 2019, as firms had to wait 90 days to file a request for suspension during this time period (independently of the hospitals' EAR status).

Figure B.5 shows a scatter plot with hospitals' exposure to prompt payment enforcement on the x-axis and the fraction of their 2019 dispatches that triggered a dispatch suspension at some point between 2019 and 2023. The fraction of dispatches that trigger a suspension is low across the board, with a median of 1.3% and a maximum of 4.7%. There is a positive correlation between hospitals' exposure and the fraction of dispatches that have triggered suspensions. The regression line, depicted in black, predicts that hospitals with exposure close to zero have, on average, only 1% of dispatches triggering a suspension. In contrast, 2% of dispatches are predicted to have triggered suspensions in hospitals with exposure close to 0.8.

[18]Focusing on the first year of the data reduces the bias that might arise from the right-censoring of the data, as suspensions are not observed after December 2023. For purchase orders associated with 2019, 93% of suspensions are recorded in 2019 and 2020, and only 0.46% of suspensions are recorded in 2023, suggesting that right-censoring is minimal for this sample of purchase orders.

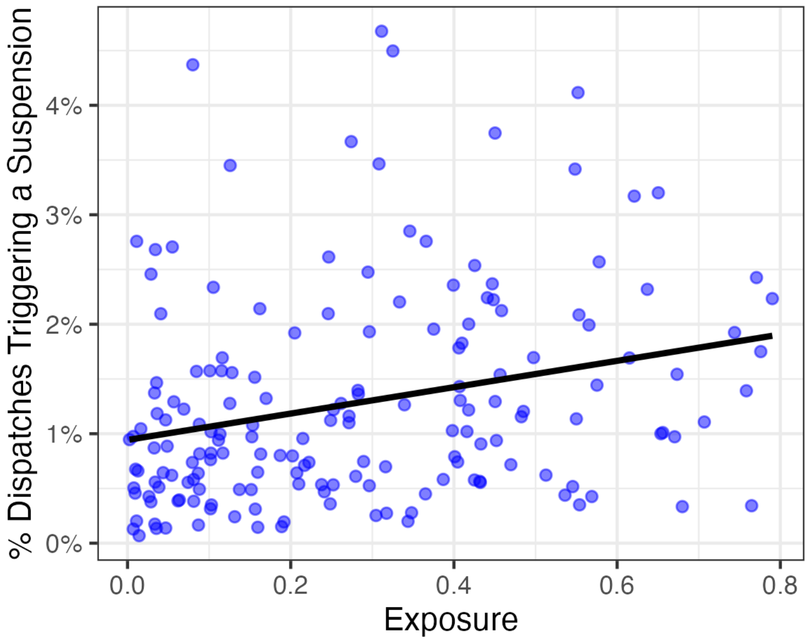


Figure B.5: Fraction of dispatches associated to 2019 purchase orders that have lead to an approved request to suspend future dispatches (y-axis) and exposure to prompt payment enforcement (x-axis).

Appendix B.3. The impact of suspensions on hospitals' drug supply

To assess the impact of suspensions on hospitals' drug supply, monthly data on dispatches by hospital and drug are combined with suspension data to estimate a staggered DiD. A unique event per hospital and purchase order is defined as the first month when an approved suspension associated with a purchase order (always associated with a single drug and supplier) was filed. Only hospital–purchase-order combinations that have such an event are retained in the sample. Months where aggregate hospital purchases from a purchase order equal zero are dropped to remove periods when purchase orders were likely inactive and hospitals could not procure from them.

Another database aggregates the event study to the hospital-drug level, as multiple suppliers can simultaneously offer a given drug through Cenabast. Here, the event is defined as the first month when an approved suspension associated with any purchase order linked to the drug in question was filed. Similarly, months where aggregate hospital purchases of a drug equal zero are dropped to remove periods when the drug was likely not available through

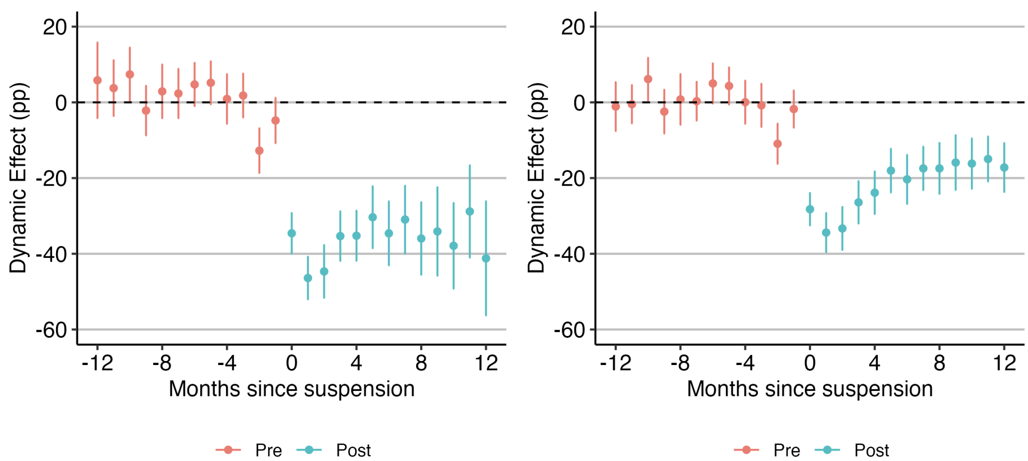
Cenabast.

The dependent variable of interest equals 100 if a hospital receives a dispatch associated with a given drug or purchase order in a given month, and zero otherwise. Hence, dynamic treatment effects can be interpreted as the probability of receiving a dispatch k periods since the suspension of dispatches. It is well known that treatment effect heterogeneity can bias Two-Way Fixed Effects estimates when the treatment is staggered (De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021). To obtain dynamic DiD estimates that are robust to treatment effect heterogeneity, the analysis that follows uses Callaway and Sant'Anna (2021)'s staggered DiD estimator. The results are shown in Figure B.6

Panel B.6a shows the results for the event study at the hospital–purchase-order level. There is no evidence of anticipation of the suspension, with a flat probability at zero for the year preceding the suspension. As expected, the suspension reduces the probability of receiving a dispatch associated with the suspended purchase order significantly, by approximately 40 percentage points. This effect is stable up to a year after the dispatch. The results suggest that a sizable share of hospitals pay the overdue bill as soon as dispatches are suspended to reinstate dispatches.

Panel B.6b shows the results for the event study at the hospital-drug level. As was the case for purchase orders, there is no evidence of anticipation. While the initial drop in the probability of receiving dispatches in the month of the suspension is only slightly smaller than the drop reported in panel B.6a, it converges to about a 20 percentage point drop after five months. This suggests that hospitals can overcome dispatch suspensions by switching to another active Cenabast provider to procure the same drug. The twenty percentage point drop that remains after a year might signal that some hospitals decide to procure a close substitute of the drug available in Cenabast (e.g., the same active component with a different concentration or formulation), or stop procuring the drug from Cenabast.

Appendix C. Supplementary Tables and Figures



(a) Purchase Order

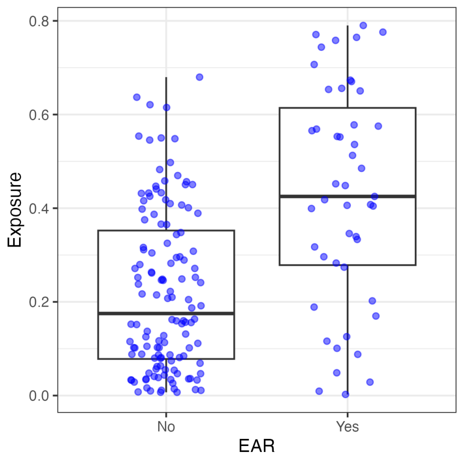
(b) Drug

Figure B.6: Callaway and Sant'Anna (2021)'s DiD dynamic estimator for the event of a dispatch suspension. Panel a shows estimates of the probability of receiving a dispatch associated to the purchase order suspended at zero, k months form the suspension. Panel b shows the same with data aggregated at the hospital-drug level. Red and blue points represent point estimates before and after the event, with vertical lines representing 95% confidence intervals. pp stands for percentage points.

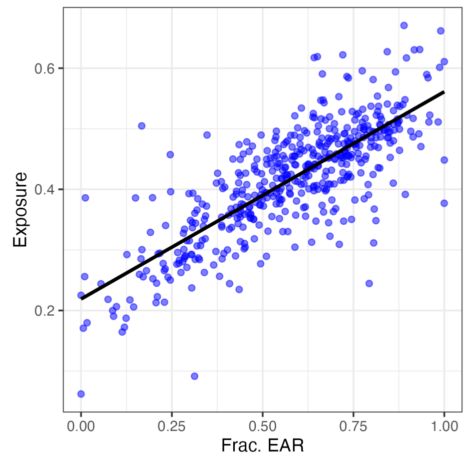
Table C.3: Average treatment effects after announcement and implementation of prompt payment enforcement mechanism—Full results

Dep. var:	log(*Avg. Days*) (1)	log(*Purchases*) (2)	log(*Prices*) (3)
$Exp \times Ann$	-0.072**	0.023	-0.072
	(0.035)	(0.025)	(0.097)
$Exp \times Imp$	-0.099**	-0.002	-0.214
	(0.042)	(0.082)	(0.152)
$EAR \times Ann$	0.090	-0.004	-0.214
	(0.084)	(0.082)	(0.133)
$EAR \times Imp$	0.239***	0.002	-0.402**
	(0.084)	(0.093)	(0.172)
$DCI \times Ann$	0.340***	-0.069	-0.219
	(0.094)	(0.060)	(0.147)
$DCI \times Imp$	0.154	0.027	-0.281
	(0.101)	(0.071)	(0.181)
Observations	871	1,041	1,824

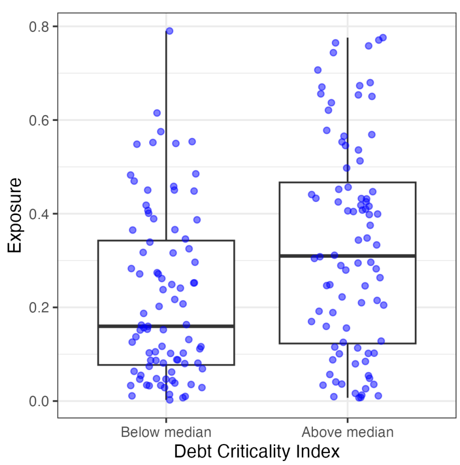
Observation level is hospital-year in columns 1 and 2, and drug-year in column 3. Standard errors clustered at the hospital (columns 1 and 2) and drug (column 3) level in parenthesis below point estimates. *Exp*, *EAR*, *DCI*, *Ann*, and *Imp* stand for Exposure, *Establecimiento Autogestionado en Red*, Debt Criticality Index, Announcement, and Implementation. Stars next to point estimates denote statistical significance: * $p< 0.1$, ** $p< 0.05$, *** $p< 0.05$.



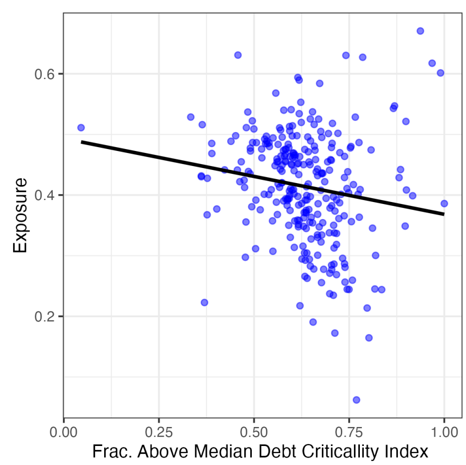
(a) Hospitals by EAR



(b) Drugs by EAR

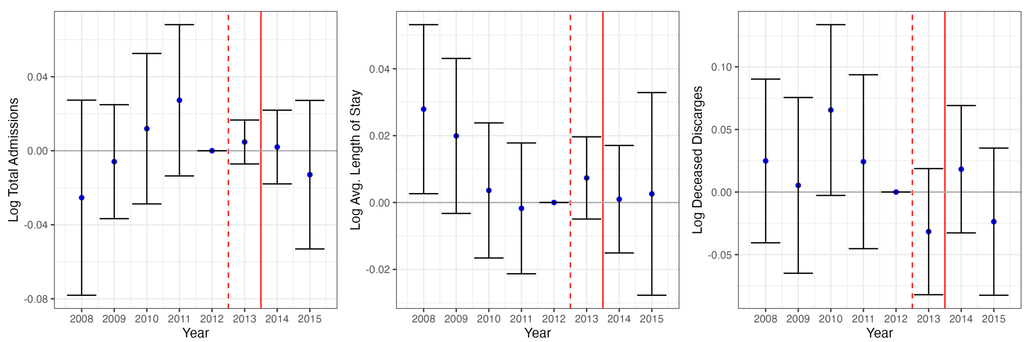


(c) Hospitals by DCI



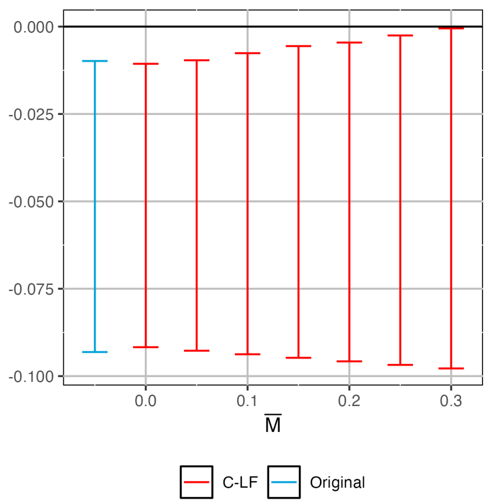
(d) Drugs by DCI

Figure C.7: Exposure to prompt payment enforcement and EAR status (panels a and b). and Debt Criticality Index (DCI, panels c and d). Panel a shows box plots for exposure to prompt payment enforcement, separately for hospitals with different levels of DCI. The lower, middle, and upper horizontal lines of the box represent quartiles, and the vertical line is the range of the data. Hospitals' exposure is represented as blue dots. Panel b displays a scatter plot of drugs' exposure to prompt payment enforcement (y-axis) against the fraction of a drug that is purchased by hospitals with DCI above the median, along a linear fit of the relationship represented by a black line. Panels c and d are analogous to panels a and b, but using the Debt Criticality index to split the sample based on whether hospitals fall above or below the median.

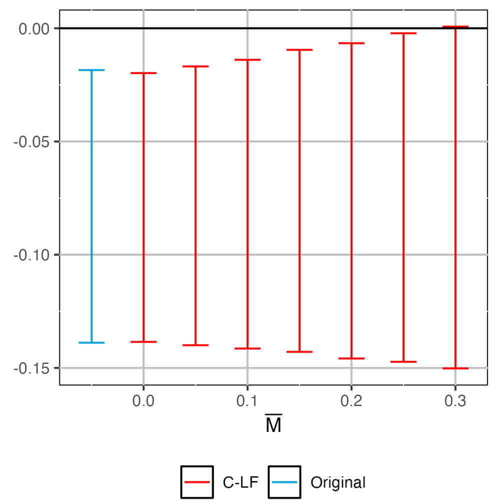


(a) (b) (c)

Figure C.8: Dynamic DiD estimates of the impact of prompt payment enforcement on total admissions (a), average length of stay (b), and deceased discharges (c). The dashed red line represents the announcement of the mechanism stepping up prompt payment enforcement, the red solid line its implementation. Blue dots represent TWFE estimates and black lines 90% confidence intervals, with standard errors clustered at the hospital level.



(a)



(b)

Figure C.9: Rambachan and Roth (2023)'s Relative Magnitude estimates for impact of announcement (a) and implementation (b) of prompt payment enforcement on average payment days. $\overline{M}$, at the x-axis label, represents the maximum allowed violation of parallel trends as a fraction of the maximum pre-treatment deviation from parallel trends. The blue vertical line at the left of each panel present the original 90% confidence interval of the estimate for reference. The red vertical lines represent partially identified sets that contain the true treatment effect with 90% confidence under the assumption that parallel trends are not violated by a larger fraction of the pre-treatment maximum deviation defined by x-axis value. C-LF stands for the Conditional Least-Favorable Hybrid method used by Rambachan and Roth (2023) to obtain a consistent estimator of the partially identified set.