Competition under Financial Constraints in Procurement Markets*

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When buyers pay late, suppliers must finance the gap between production and payment—a cost that falls hardest on financially constrained firms. We study how such financial constraints shape entry, bidding, and allocation. We use rich administrative data and exploit a reform that cut payment delays in Chilean public health procurement. Difference-in-differences estimates show that, after the reform, auctions held by buyers that used to pay late attracted more bids, mostly from small firms, and were awarded at prices about 4 percent lower. To separate lower financing costs from increased competition, we estimate a model of entry and bidding in scoring auctions in which expected delays act as a firm-specific financing wedge. The monthly cost of liquidity is 1.0 percent (12.5 percent annualized) for small firms and 0.4 percent (5.4 percent) for large firms. Financing costs account for up to a fifth of the cost gap between small and large firms. We use the model to decompose market effects and simulate counterfactuals. Together, the results suggest that payment terms, and policies that ease suppliers' financing more broadly, are a lever over market performance. JEL Codes: D22, D44, G32, H57.

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1 Introduction

Suppliers typically produce before they are paid and must finance the gap between production and payment (Petersen and Rajan, 1997; Klapper et al., 2012). Payment delays therefore raise suppliers' effective costs, particularly for financially constrained firms, whose cost of liquidity is higher (Murfin and Njoroge, 2015; Barrot, 2016; Barrot and Nanda, 2020). By altering firms' relative costs, payment delays can shape whether firms enter a market, how aggressively they compete, and ultimately prices and the allocation of output across firms.

Although practitioners and policymakers recognize that late payments shape competition (National Audit Office, 2015; European Commission, 2023), identifying their effects is difficult: it requires a compelling research design to distinguish financing costs from other unobserved costs and account for simultaneous changes in market equilibrium. We address these challenges by combining a government-wide reform that sharply reduced payment delays with administrative data and a model of entry and bidding.

Our setting is public procurement in the Chilean health sector, where over 200 buyers—mostly public hospitals—purchase about USD 2 billion per year (0.5 percent of GDP) from roughly 15,000 suppliers through scoring auctions on a centralized platform, Mercado Público. Our administrative data follow contracts from auction through invoice payment and link suppliers to tax records, allowing us to observe payment delays alongside participation, bids, prices, and firm characteristics.

We exploit a 2020 reform in which the government changed its financial management software to automate invoice payments from the Treasury's account in 30 days. Before the reform, public health entities paid suppliers on average more than 80 days after contract completion, and delays varied widely across buyers: about one-fourth paid within 30 days on average, while the majority paid well beyond 30 days, often delaying by several months.

These differences in pre-reform payment delays provide the basis for our identification strategy. The reform sharply shortened delays for historically late-paying buyers, while leaving delays largely unchanged for buyers that already paid promptly. Before the reform, payment delays followed parallel trends across the two groups; afterward, average delays fell by approximately 50 days for late payers relative to early payers.

Using a Difference-in-Differences approach, we estimate the impact of payment delays on four key outcomes: firms' auction participation decisions, bidding behavior, winning probabilities, and contract prices. By analyzing these margins, we can quantify whether firms internalize payment delays in their behavior and its role in shaping procurement market outcomes. Furthermore, we allow for a rich heterogeneity in the effects based on firm contract characteristics to accommodate potential asymmetries in underlying financial constraints.

We find that reducing payment delays increases firm participation by 15%, especially by small

firms. It also stimulates more aggressive bidding behavior, and a reduction in contract prices of about 4%. Effects are larger for contracts with greater liquidity needs, consistent with financing costs limiting participation and weakening suppliers' competitiveness.

The decline in prices reflects changes in both suppliers' costs and equilibrium markups. Faster payment lowers the cost of financing a contract, particularly for financially constrained firms. At the same time, it changes suppliers' relative costs and incentives to enter, altering the competitive pressure they face and the markups they charge. The reduced-form estimates capture the combined effect of these forces but do not reveal how much of the price decline comes from lower costs relative to lower markups. To separate these channels and evaluate counterfactuals, we develop and estimate a model of entry and bidding in scoring auctions.

The model follows the life cycle of a procurement contract. Potential suppliers decide whether to enter an auction before learning their production costs. Entrants then observe their costs and submit bids, and the buyer awards the contract according to its scoring rule. The winner incurs its production cost at delivery but receives payment only after a stochastic delay. It therefore discounts the promised payment at its own cost of liquidity. Together, the firm's cost of liquidity and the buyer's payment-delay distribution determine a firm-specific financing wedge that raises the effective cost of supplying the contract and, holding competitors' behavior fixed, lowers the expected return to entry. In equilibrium, entry also responds to changes in rivals' costs and participation decisions.

We estimate the model on roughly 200,000 auctions for pharmaceutical products held between 2016 and 2024. For each auction, we define a set of potential bidders as firms active in the product market and region that have a meaningful probability of bidding. Estimation proceeds in two steps. The first step separates changes in competition from changes in effective costs: we predict equilibrium entry probabilities for each potential bidder, and we invert bidders' first-order conditions to recover effective costs (Guerre et al., 2000; Athey and Haile, 2007). The second step separates production costs from the financing wedge. Our unusually large and rich auction dataset supports a detailed specification of firm costs: production costs depend on firm, buyer, product, and time fixed effects and auction characteristics, while the cost of liquidity varies across delay horizons and with firm characteristics. The liquidity wedge is identified from the reform-induced shifts in buyers' delay distributions, under the assumption that, absent the reform, production costs would have evolved in parallel across buyers with different pre-reform delays. Finally, observed entry choices and the recovered expected profits identify the distribution of entry costs.

The estimated cost of liquidity is substantial and differs across firm sizes. A specification imposing a constant monthly rate yields an average cost of liquidity of 0.9 percent per month, or 11 percent annualized. Small firms face 1.0 percent per month (12.5 percent annualized), compared with 0.4 percent (5.4 percent) for large firms. Allowing rates to vary across delay horizons reveals that longer delays are disproportionately costly for small firms: their monthly cost of liquidity

increases with the length of the delay, whereas that of large firms remains roughly constant.

These estimates show that payment delays contribute to cost differences across firms. Small firms' production costs are about 5 percent higher than those of large firms, and financing costs under pre-reform payment delays widen this gap by a further 1.1 percentage points, accounting for roughly one-fifth of the total effective-cost gap. The recovered effective costs also allow us to decompose the reform-induced decline in bids: in auctions held by severe late payers, about 70 percent reflects lower effective costs and the remainder lower markups.

We then use the model to simulate market equilibrium in a sample of auctions held by late payers in 2019 under two counterfactuals in which financing costs are eliminated. In the first, we remove the financing wedge from firms' bidding problems while holding entry probabilities fixed at their baseline values. This isolates the bidding response: median bids fall by 1.7 percent for small firms and 1.2 percent for large firms, as small firms benefit more from the removal of the wedge, and the predicted auction price falls by 1.5 percent. In the second, we also let firms' entry decisions respond in equilibrium. Large firms become less likely to enter, by 2.2 percentage points, while small firms' entry barely changes. Eliminating financing costs therefore improves small firms' competitive position both by narrowing cost differences and by shifting the composition of entrants toward them.

Together, these findings show that payment delays raise suppliers' effective costs and widen cost asymmetries across firms. These changes reshape equilibrium entry and bidding, affecting the prices buyers pay and the allocation of contracts across suppliers. More broadly, policies that reduce financing costs—such as subsidized loans, improved access to factoring, and prompt-payment requirements—should be evaluated for both their direct benefits and their equilibrium effects on competition and allocation. Moreover, such policies may offer relatively unexplored levers for competition policy.

Our paper contributes to three strands of literature. First, we contribute to the literature on trade credit and firms' financial constraints (Barrot, 2016; Breza and Liberman, 2017; Barrot and Nanda, 2020) and its connection to product-market competition (Chevalier, 1995; Chevalier and Scharfstein, 1996). This work shows that payment timing affects firms' entry, survival, employment, and organization, and that financial conditions shape firms' pricing and their rivals' competitive responses. While part of this literature studies financial constraints through access to external finance, we recover suppliers' marginal cost of liquidity from their entry and bidding responses to payment delays. This cost reflects the funds used at the margin, whether external borrowing or internal resources with an opportunity cost. We estimate how liquidity costs vary across horizons and firms, contribute to cost asymmetries, and shape market equilibrium.

Second, we contribute to the empirical literature on procurement auctions with entry and cost asymmetries (Li and Zheng, 2009; Athey et al., 2011; Campo et al., 2003). Related work by Marion and Rosa (2025) shows how contractors front-load bids toward work paid earlier, revealing

heterogeneous preferences for payment timing. We identify financing costs as a source of bidder cost heterogeneity and use reform-induced variation in payment delays, together with entry and bidding decisions, to separate changes in costs from changes in equilibrium markups.

Third, we relate to the literature on procurement design and small-business preferences (Marion, 2007; Krasnokutskaya and Seim, 2011; Athey et al., 2013), which studies auction rules, bid preferences, and participation requirements as levers to shape who competes for public contracts. Reducing financing costs offers a complementary approach: it shifts contracts toward small firms by removing a friction that raises their costs, while preserving the award rule.

The rest of the paper is organized as follows. Section 2 describes the setting, the payment reform, and the data. Section 3 presents the effects of the reform on procurement outcomes. Section 4 develops the model, Section 5 describes its estimation and results, and Section 6 presents the counterfactuals. Section 7 concludes.

2 Context

2.1 Public Health Procurement and Payment Reform

Government entities in Chile are required to contract with firms through a single centralized online platform, Mercado Público. In the health sector, 207 procurement entities—mostly public hospitals, henceforth *buyers*—purchase about USD 2 billion per year (0.5% of GDP) from roughly 15,000 firms, henceforth *suppliers*.[1] Most purchases occur through open auctions (*licitaciones públicas*): the buyer posts its requirement on the platform, and any registered firm may submit a bid. These are scoring auctions whose rules are designed by each buyer (Asker and Cantillon, 2008; Allende et al., 2024, 2025). The score is linear in the price and in a set of non-price attributes, and the contract is awarded to the bidder with the highest score.[2] Besides price, the scoring rule rewards technical attributes—such as quality certifications, bioequivalence, and the firm's market experience—as well as delivery terms.[3] In the pharmaceutical auctions we study, price accounts on average for 50% of the total score, technical attributes for 35%, delivery for 10%, and other criteria for 4%. The lowest bid wins in roughly three-quarters of auctions.

Once the tender is awarded, the buyer issues a purchase order that sets the terms of the contract, and the awarded supplier delivers the goods or services. Once the goods or services are delivered, the supplier issues an invoice. The buyer then recognizes the invoice reception and subsequently

[1] We focus on the health sector, among other reasons, because its buyers were by far the most likely to pay late before the reform compared with the rest of the central government.

[2] The price component typically follows an inverse rule of three, assigning each bidder the ratio between the lowest submitted price and its own price.

[3] Other dimensions, such as post-sale service, social, and environmental criteria, receive little weight on average. Non-price attributes largely reflect product characteristics and the supplier's track record, which are mostly determined before the auction.

pays.[4] Delays in payments have been a recurring theme in public opinion and in public policy discussions.[5] This is partly because a stated objective of public procurement policy in Chile, as in many other countries, is to promote competition and, in particular, the participation of small and medium-sized enterprises (SMEs), which are typically perceived as more financially constrained and thus more sensitive to payment delays.

Payment Reform. In 2020, the central government modified the financial management software that public entities use to process payments. After the modification, procurement-related payments were taken out of the hands of individual buyers: once a buyer acknowledges the receipt of an invoice, the supplier is paid automatically 30 days later, directly from a central account managed by the Ministry of Finance, which then charges the buyer for the corresponding amount. The stated justification for the reform was precisely to "avoid liquidity issues for government suppliers, particularly small and medium enterprises."[6] The reform was rolled out gradually, with 95% of health-sector buyers incorporated between April and August 2020. In March 2023, the government temporarily suspended automatic payments after the Comptroller flagged erroneous duplicate payments during the roll out in 2020. Automatic payments resumed in May 2023, although health services were reinstated gradually.[7] Appendix C describes the pre-reform payment rules, the announcement of the reform, the rollout, and the 2023 interruption in more detail.

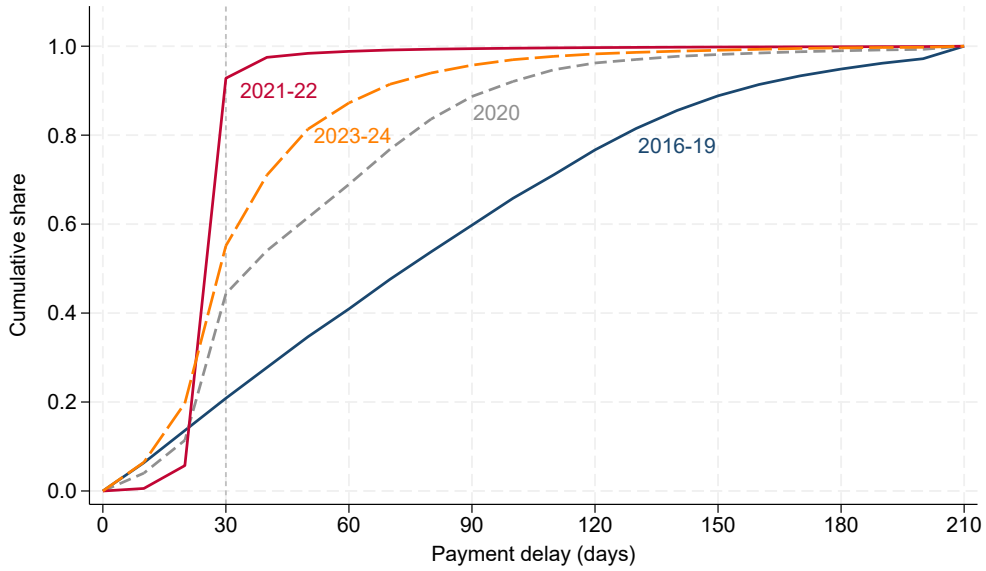
The reform sharply changed the distribution of payment delays, as shown in Figure 1. Before the reform, only 21% of invoices were paid within 30 days, 40% were paid after more than 90 days, and the average delay was about 80 days. During the 2020 rollout, the share paid within 30 days rose to 44%. Once the new system was fully in place, in 2021–2022, the distribution collapsed around the 30-day deadline: 93% of invoices were paid within 30 days. The 2023 interruption partially reversed these gains. In 2023–2024, the share paid within 30 days fell back to 55%, but long delays remained rare—only 4% of invoices were paid after 90 days—and the average delay, at about 36 days, stayed well below its pre-reform level.

[4]The Chilean procurement regulation requires buyers to pay their suppliers within 30 days of recognizing the reception of an invoice. Buyers in the health sector have an additional 15 days for a maximum payment delay of 45 consecutive days. If payments are delayed, suppliers can file a complaint to the procurement agency (*ChileCompra*), which generates statistics of buyer complaints. However, no further internal procedure enforced prompt payments.

[5]For example, the president of the Confederation of Retail Trade (Confedech), Rafael Cumsille, told La Tercera in 2018 *"We congratulate ChileCompra and the Comptroller for their determination to do justice to the thousands of suppliers, especially small size enterprises because it is enough that buyers have the flexibility to pay when they want, seriously affecting small suppliers" (link)*. Trinidad Inostroza, former ChileCompra director, pointed out in 2017 that the percentage of invoices paid late in 2016 reached 40%, and in the health sector, this figure reached 65%. She pointed out that there are various bureaucratic obstacles and financing problems that explain these delays, which *"should not happen, because they should not purchase if they cannot pay on time (...) we have a special concern for these smaller companies since they do not have the financial capacity to be able to wait for long payment periods when they have complied"* (link)

[6]See Norm by the Budget Director. The government refers to the new system as the *Plataforma de Pagos Centralizados* (Centralized Payment Platform), PPC, or Plataforma de Pagos Automáticos (Automatic Payment Platform), PPA. The modification could be implemented due to the prior adoption of electronic invoicing, which allowed invoice information

Figure 1: Distribution of payment delays by phase of the reform



Notes: The figure plots the cumulative distribution of payment delays—the number of days between the buyer's acknowledgment of an invoice and its payment—pooling all invoices paid by public health buyers in each period. Periods are defined by the year of payment and correspond to the phases of the reform: 2016–2019 is the pre-reform period; 2020 is the rollout year, in which buyers were gradually incorporated into the new system and automatic payments applied only to new contracts; 2021–2022 is the post-reform period, with the system fully in place; and 2023–2024 is the post-reform period including the March 2023 interruption of automatic payments and the gradual reinstatement of buyers that followed. The vertical line marks the 30-day deadline. Delays are measured in 10-day bins and truncated at 210 days.

2.2 Data

We combine administrative records that cover the full life-cycle of public contracts—from the auction to the payment of the supplier—for 2016–2024. The data come from three sources: auctions and purchase orders from the procurement platform, payments from the government's financial management system, and firm characteristics from the tax authority. Records are linked across sources through unique auction and purchase-order identifiers and through the national tax ID of buyers and suppliers.

Auctions. Our data include all auctions carried out on Mercado Público. For each auction, we observe the buyer, the procurement modality, key dates, the product item required, the quantity required, and other attributes. We also observe the linear scoring rule announced by the buyer. For bidders, we observe its identity, price offer, and award status. We also use evaluation matrices digitized in a previous study to recover each bid's non-price attributes—classified as technical, delivery, and other—and total score.

to flow directly to the Ministry of Finance.

[7] As of July 2024, only 5 of the 33 regional Health Services—the administrative units on which hospitals and local purchasing units depend—had been reinstated.

Purchase orders. Once an auction is awarded, the buyer issues a purchase order (PO) to the supplier specifying the products, quantities, unit prices, and total value. Each PO carries a unique identifier and the identifier of that auction, which allows us to link awarded items to the resulting contracts.

Payments. Payment records come from the government's financial management system (SIGFE, for *Sistema de Información para la Gestión Financiera del Estado*). We observe the paying entity, the tax ID of the recipient, the PO identifier, and the dates at which the invoice was acknowledged and the payment was made. We define the *payment delay* as the number of days between the buyer's acknowledgment of the invoice and the payment.

Firms. We match suppliers to administrative records from the Chilean tax authority, which report annual sales, number of employees, age, and location for all firms filing taxes in Chile.[8] We use these data to classify firms by size following the official categories (micro, small, medium, and large). The tax data also identify each firm's legal-entity owners, which allows us to determine whether a supplier belongs to a larger corporate group—a feature that may relax its financial constraints.

Analysis samples. Even though part of our reduced-form analysis—on payment delays and on participation in auctions—uses all purchases by public health entities. Most of the analysis, however, focuses on auctions for pharmaceutical products, and the structural model is estimated exclusively on this sample. Pharmaceuticals are well suited to our analysis because they are standardized and can be precisely identified through the national drug classification (ZGEN), which records each product's active ingredient, therapeutic class, dosage form, and concentration (for example, losartan—an antihypertensive—in 50 MG tablets). This allows us identify units precisely (e.g., one tablet) and compare unit prices across contracts for the same product.

Auctions are run at the drug level, where there is room for substitution between sellers but not between molecules or dosages. Moreover, for each auction, we define a set of *potential bidders* as the set of firms that are active suppliers in the product market (see, e.g., Athey et al., 2011; Krasnokutskaya and Seim, 2011), and *actual bidders* are those that submit an offer in the auction.[9]

[8] About 6% of the suppliers in our sample are registered as natural persons rather than legal entities. Because they file taxes as individuals, firm-level records on sales, employment, and ownership are not available for them, and we treat them as a separate category in our analysis, and assume they are small firms when grouping by size.

[9] We exclude auctions with more than one winner, with missing or outlying winning bids, or with fewer than five potential bidders, as well as products and buyers with very few auctions. Section 4 and Appendix E.1 describe the construction of the set of potential bidders and the sample restrictions in detail.

2.3 Descriptive Statistics

Buyers and payment delays. Before the reform, buyers differed widely in how long they took to pay their suppliers. In 2019, the average buyer paid 63 days after acknowledging an invoice, and the median buyer 59 days (Figure A.1 shows the full distribution). About one-third of buyers paid within 45 days on average, 42% took between 45 and 90 days, and 24% took more than 90 days.

To understand what drives these differences, we decompose the variation in payment delays across purchase orders. Table B.2 regresses the (log) payment delay of each purchase order paid in 2016–2019 on its (log) amount and adds fixed effects sequentially, so that the increase in the adjusted R^2 at each step measures how much of the variation the new dimension explains. Order size and year-month fixed effects explain little (adjusted R^2 of 0.07).[10] Buyer fixed effects are the most important dimension, adding 26 percentage points, and supplier fixed effects—which capture the selection of particular suppliers into late-paid transactions—add a further 20. Product fixed effects add less than one point, and buyer-supplier fixed effects add only 7 (column 6), which rules out a substantial role for match effects or preferential treatment of specific suppliers. Payment delays are thus primarily an attribute of the buyer that seems to apply to all of its suppliers. Table B.1 compares early and late payers in 2019. Late payers are larger hospitals and treat patients with longer average stays. They also make larger purchases, and their auctions attract fewer bidders (3.7 versus 4.2 on average) and a smaller share of bidders and winners that are micro, small, or medium enterprises.

Suppliers. The pharmaceutical sample includes 494 firms. Firms are heterogeneous and the size distribution is skewed: the median firm has 9 employees and annual sales of USD 0.7 million, whereas the averages are 96 employees and USD 9 million (Table B.3). About 7% of suppliers are natural persons, and almost three-quarters are located in the Santiago Metropolitan Region. Public procurement is a relevant market for many of these firms, it accounts for 29% of total annual sales for the average firm. Larger firms are present in more markets, participate more, and win more often (Table B.4, by quartile of 2019 sales). Top-quartile firms account for 59% of potential-bidder observations and bid in 33% of their auctions, compared with 10% in the bottom quartile; conditional on bidding, they win 26% of the time, compared with 6–14% in the other quartiles. Bids decline monotonically with size: for the same product, top-quartile firms bid 21 log points below bottom-quartile firms.

Auctions. The sample includes roughly 200 thousand auctions for 1,135 products, held between 2016 and 2024. The average auction has 30 potential bidders, of which 4.7 submit a bid, for an

[10] Payment delays display a seasonal pattern (Figure A.2). Purchase orders issued in the first half of the year were paid after about 90 days on average, whereas those issued in October and November, close to the end of the fiscal year, were paid after about 50 days.

average entry rate of 16% (Table B.5). Price accounts on average for 50% of the total score, technical attributes for 35%, delivery for 10%, and other criteria for 4%. Although non-price attributes carry substantial weight, they vary relatively little across bidders: the average bidder obtains 79% of the maximum technical score and 91% of the maximum delivery score, and the median bidder obtains the maximum in both (Table B.6).[11] As a result, the lowest price bid wins in 73% of auctions.

3 The Effect of Payment Delays

This section studies the effects of reducing payment delays on procurement outcomes. As described in Section 2.3, the payment reform imposed 30-day payment delay on all public health buyers. We interpret the reform as a buyer-specific shock to payment delays: it shortened delays sharply for buyers that used to pay late and left essentially unchanged those that already paid on time. We exploit this variation to provide evidence of the effects of payment delays on auction participation and contract prices. These results will be the basis for our model in Section 4.

3.1 Empirical Strategy

We classify buyers according to their average payment delay in 2019, the last year before the reform. *Early payers* are buyers whose average delay was 45 days or less, the maximum allowed for the health sector; *moderate late payers* had average delays between 45 and 90 days; and *severe late payers* had average delays above 90 days. Because payment delays are mostly a persistent attribute of the buyer (Section 2.3), this classification captures each buyer's exposure to the reform: the more a buyer delayed payments before 2020, the larger the reduction in delays that the 30-day rule imposed on it.

We estimate the following dynamic difference-in-differences specification:

$$y_{ikt} = \alpha_i + \delta_k + \eta_t + \sum_{g \in \{M,S\}} \sum_{\tau \neq 2019} \gamma_{g\tau} \cdot \mathbb{1}\{G_i = g\} \cdot \mathbb{1}\{t = \tau\} + \varepsilon_{ikt}, \tag{1}$$

where y_{ikt} is an outcome for buyer i, product k, and year t; α_i, δ_k, and η_t are buyer, product, and year fixed effects; and $G_i \in \{E, M, S\}$ indicates whether buyer i was an early, moderate late, or severe late payer in 2019. The coefficients $\gamma_{g\tau}$ measure the change in the outcome for late payers of group g relative to early payers between year τ and 2019, the omitted year. Identification relies on the assumption that, absent the reform, outcomes would have evolved in parallel across groups of buyers, which we assess through the pre-reform coefficients ($\tau < 2019$). We also report a static version of equation (1) that replaces the year interactions with a single post-reform indicator.

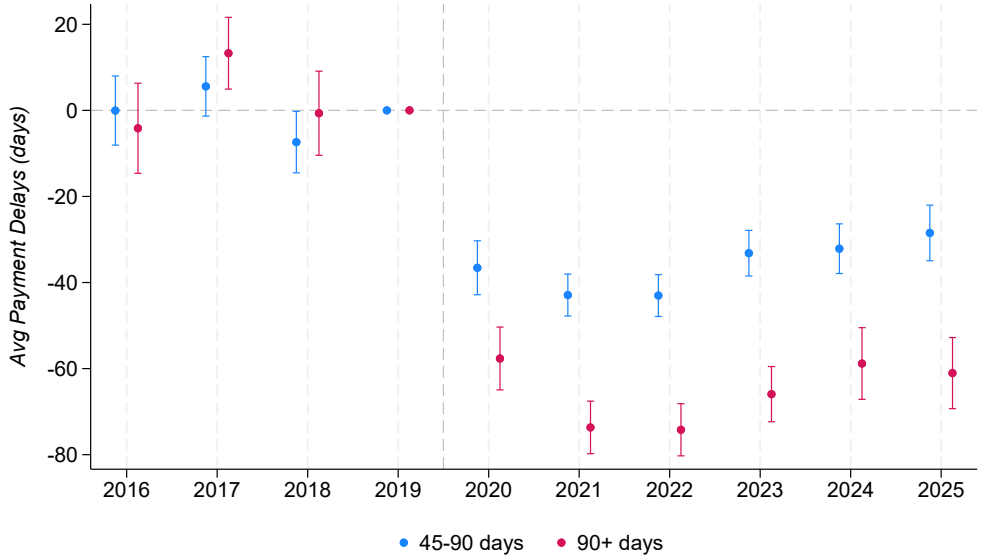
[11] The technical score most often rewards quality certifications (74% of auctions), bioequivalence (53%), and market experience (47%) (Table B.7).

We estimate equation (1) on two samples (Section 2.2). Effects on payment delays and on participation use all purchases by public health buyers. For participation, the unit of observation is the auction, products are defined at the six-digit level of the UNSPSC classification, and we also control for the type of procurement procedure. Effects on prices use pharmaceutical auctions, for which products are precisely defined and prices are comparable across contracts.

3.2 Effects on Payment Delays

Figure 2 shows that the reform achieved its goal. Before 2020, payment delays evolved similarly across the three groups of buyers. Starting in 2020, delays fell sharply for late payers relative to early payers: by about 40 days for moderate late payers and by 60–75 days for severe late payers. The reduction appears in the year of the rollout, reaches its maximum in 2021–2022, and is partially reversed after the 2023 interruption of automatic payments, although delays remain well below their pre-reform levels. The reform thus generated large, buyer-specific changes in payment delays, which we use to study how suppliers respond.

Figure 2: Effect of the reform on payment delays



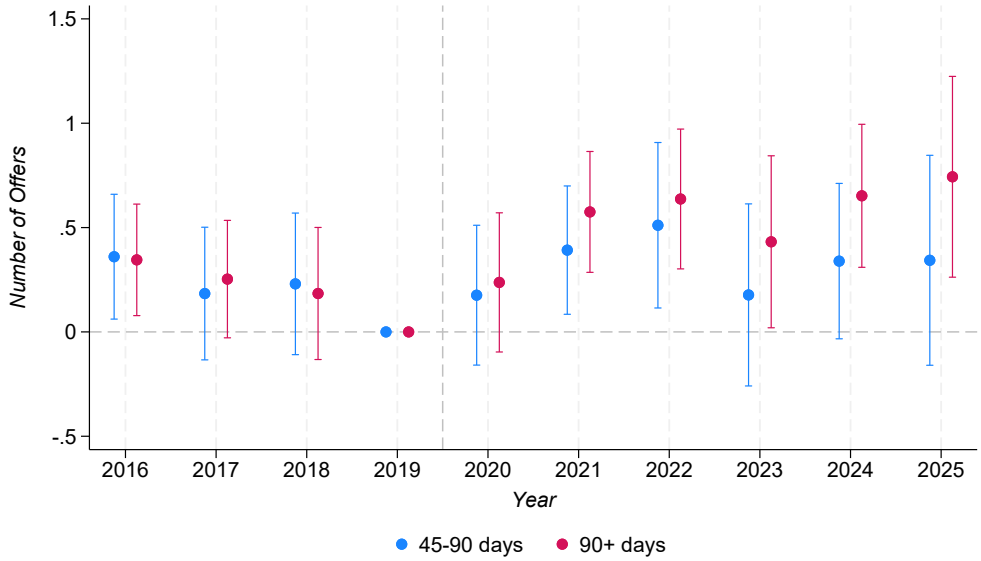
Notes: Estimates of $\gamma_{g\tau}$ from equation (1), with 95% confidence intervals. The outcome is the average payment delay, in days. Moderate late payers (45–90 days) and severe late payers (more than 90 days) are compared with early payers (45 days or less), based on buyers' amount-weighted average payment delay in 2019, the omitted year. Buyer and year fixed effects; standard errors clustered by buyer-year.

3.3 Effects on Participation and Prices

Effects on participation. Shorter payment delays made auctions more attractive to suppliers. Figure 3 shows that, after the reform, the number of offers per auction increased among late payers

relative to early payers. The effect builds up over time and is larger for severe late payers, whose auctions received about 0.6 more offers per auction in 2021–2022. The increase in participation is concentrated among small firms (Figure 4), consistent with the idea that payment delays are more costly for financially constrained suppliers.

Figure 3: Effect of the reform on the number of offers per auction



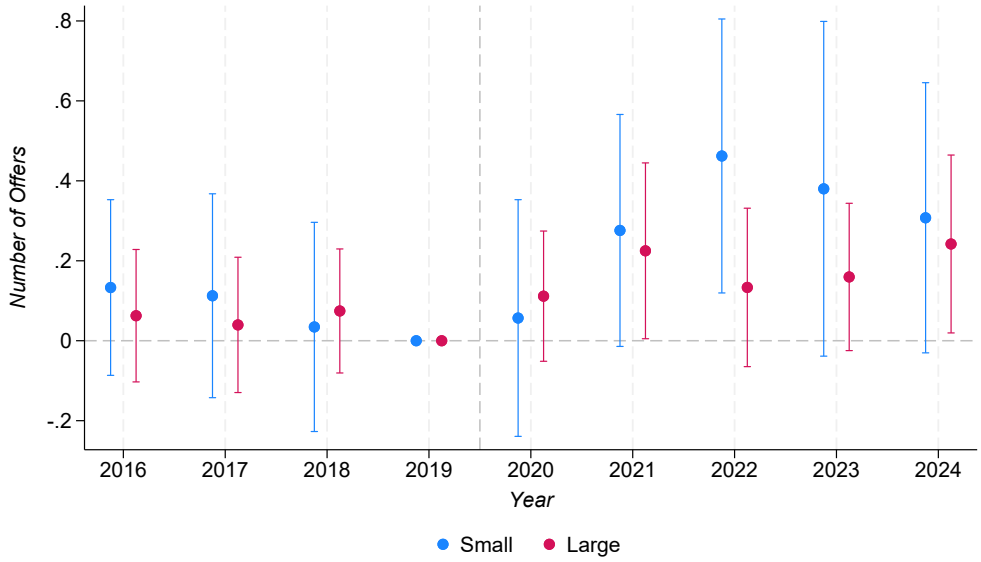
Notes: Estimates of $\gamma_{g\tau}$ from equation (1), with 95% confidence intervals. The outcome is the number of offers received by an auction. All auctions by public health buyers. Buyer, year, procedure-type, and product (six-digit UNSPSC) fixed effects; standard errors clustered by buyer-year.

Effects on prices. The increase in participation was accompanied by lower prices. Figure 5 reports the effect of the reform on the log winning bid in pharmaceutical auctions, comparing auctions for the same product held by the same buyer before and after the reform. The pre-reform coefficients are small and statistically insignificant, which supports the parallel-trends assumption. After the reform, winning bids fell for both groups of late payers relative to early payers, by about 4% in 2021–2022 and up to 6% in 2023. In the static specification, the reform reduced winning bids by 3.5% in auctions held by moderate late payers and by 4.0% in those held by severe late payers, both significant at the 1% level.

3.4 Heterogeneous Effects and Other Outcomes

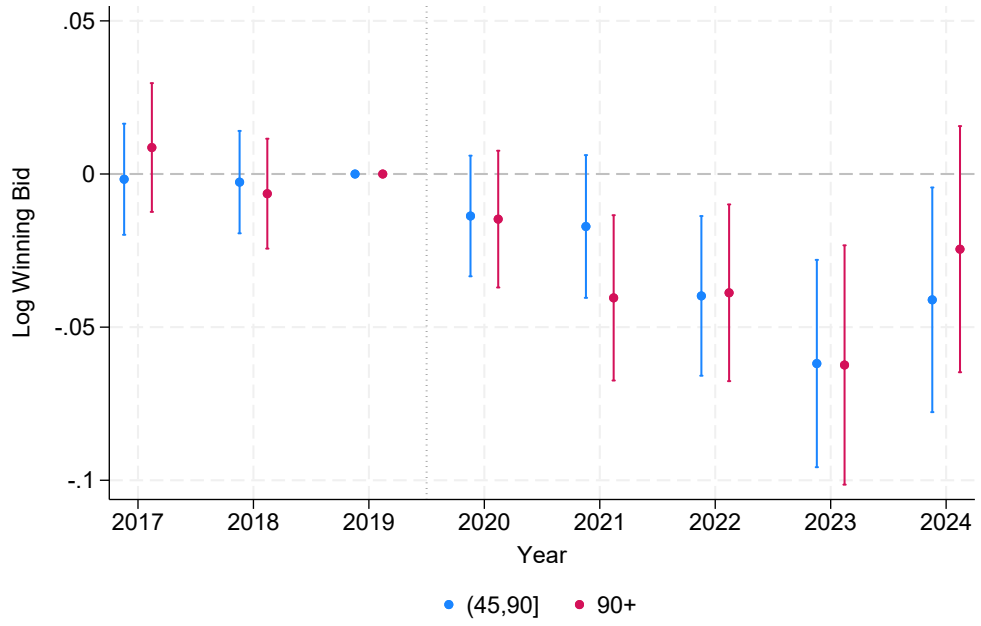
Heterogeneous effects. The increase in participation is largest in medium-sized contracts (Appendix Figure A.3). Effects are also larger in product categories with a high presence of small and medium enterprises, such as medical supplies and office materials.

Figure 4: Effect of the reform on the number of offers, by firm size



Notes: Estimates of the effect of the reform on the number of offers per auction submitted by firms of each size category. Late payers are buyers whose 2019 amount-weighted average payment delay exceeded 30 days. Fixed effects and standard errors as in Figure 3.

Figure 5: Effect of the reform on winning bids, pharmaceutical auctions



Notes: Estimates of $\gamma_{g\tau}$ from equation (1), with 95% confidence intervals. The outcome is the log winning bid per unit. Pharmaceutical auctions in the model sample. Buyer-by-product, year, procedure-type, and quarter fixed effects, and log quantity; standard errors clustered by buyer-product.

Other outcomes. We find no evidence that buyers responded to the reform in ways that could confound the effects above. First, buyers did not delay the acknowledgment of invoices, which starts the 30-day clock under the new system (Appendix Figure A.4). Second, the reform did not change the procurement channel: the share of goods purchased through auctions rather than direct purchases remained stable. Third, we find no evidence that buyers changed the weight assigned to price in the scoring rule of their auctions. Finally, we find no clear effects of the reform on hospital use or health outcomes.

3.5 Discussion

To summarize, the payment reform sharply reduced payment delays for buyers that used to pay late. Auctions held by these buyers attracted more offers, particularly from small firms, and were awarded at lower prices. These results suggest that payment delays act as a cost for suppliers, and that this cost is larger for firms with less access to finance.

While this evidence is informative about the effects of payment delays on procurement outcomes, it cannot separate the two channels behind the price decline: shorter delays lower the financing cost of a contract, which firms pass through to their bids, and they attract additional bidders, which intensifies competition and lowers markups. Both of these channels contribute to the observed price reduction. Moreover, the reduced-form analysis does not allow us to evaluate outcomes under alternative payment policies. To address these questions, we develop and estimate a model of entry and bidding in Section 4.

4 A Model of Entry and Bidding with Payment Delays

We develop a model of entry and bidding in procurement auctions in which suppliers finance the gap between delivering a contract and being paid. The goal is to recover each firm's cost of payment delays and to separate the channels through which shorter delays affect entry, bids, and prices. We estimate the model with the data described in Section 2.2 and exploit the variation in payment delays induced by the reform (Section 3). Section 4.1 describes the environment, Section 4.2 introduces the cost of financing payment delays, and Sections 4.3 and 4.4 characterize the bidding and entry decisions.

4.1 Environment

The model features public buyers indexed by i, products indexed by k, and firms indexed by j. Buyer i procures product k at time t through a scoring auction, which we index by (i, k, t). The buyer specifies the quantity, the delivery conditions, and the scoring rule used to evaluate offers. Each auction has a set of potential bidders $\mathcal{J}_{ikt}$, the firms that could supply product k to buyer i at

time t, which we take as given. A subset of these firms, $J_{ikt} \subseteq \mathcal{J}_{ikt}$, enters the auction and submits bids.

Scoring rule. The buyer awards the contract to the entrant with the highest score. For entrant j with price bid $b_{j,ikt}$ and non-price attributes $\mathbf{x}_{j,ikt} = (x^T_{j,ikt}, x^D_{j,ikt}, x^O_{j,ikt})' \in [0,1]^3$ (technical, delivery, and other criteria), the score is

$$S(b_{j,ikt}, \mathbf{x}_{j,ikt}; \mathbf{w}_i) = \frac{\min_{\ell \in J_{ikt}} b_{\ell,ikt}}{b_{j,ikt}} + \delta(\mathbf{x}_{j,ikt}; \mathbf{w}_i), \qquad \delta(\mathbf{x}_{j,ikt}; \mathbf{w}_i) = \frac{1}{w^P_i} \mathbf{w}_i' \mathbf{x}_{j,ikt}, \tag{2}$$

where w^P_i is the weight on price, $\mathbf{w}_i = (w^T_i, w^D_i, w^O_i)'$ are the weights on non-price attributes, and $w^P_i + w^T_i + w^D_i + w^O_i = 1$. Equation (2) normalizes the scoring rule described in Section 2.3 by the weight on price. Only price is strategic: non-price attributes are drawn from a known distribution $H_{j,ikt}$ and are observed ex post.

Timing. The auction unfolds in three stages:

1. *Entry.* Each potential bidder $j \in \mathcal{J}_{ikt}$ privately observes an entry cost $\kappa_{j,ikt} \sim G_{\kappa,j,ikt}$ and simultaneously decides whether to enter, $E_{j,ikt} \in \{0,1\}$. Firms do not observe the realized set of entrants before bidding.

2. *Bidding.* Each entrant $j \in J_{ikt}$ privately observes a unit production cost $c_{j,ikt} \sim F_{c,j,ikt}$ and submits a bid $b_{j,ikt}$. The contract is awarded according to equation (2).

3. *Payment.* The winner incurs the production cost $c_{j,ikt}$ at delivery, in period t, and receives the payment $b_{j,ikt}$ in period $t + T_{it}$, where T_{it} is a stochastic payment delay.

The payment delay T_{it} takes values in a discrete set of months $\mathcal{T} = \{1, 2, \dots\}$, with probabilities $s_{it}(\tau) \equiv \Pr(T_{it} = \tau)$. Firms know the delay distribution of buyer i at time t when they decide to enter and bid, but not the realized delay. We treat $s_{it}(\cdot)$ as given to the auction: it is a property of the buyer's payment process, which, as shown in Section 2.3, is largely persistent within buyers and does not depend on the identity of the supplier. The reform shifted $s_{it}(\cdot)$ by different amounts across buyers, depending on their pre-reform payment distributions.

4.2 The Cost of Financing Payment Delays

Marginal cost of liquidity. The winner pays the production cost $c_{j,ikt}$ at delivery but receives the payment $b_{j,ikt}$ only T_{it} periods later. Until the buyer pays, the firm funds the contract with internal or external funds. Let $\rho_j(\tau) \geq 0$ denote firm j's marginal cost of liquidity over τ periods: the rate at which the firm values one dollar shifted from period t to period $t + \tau$.[12] This rate summarizes the

[12] Because public buyers in our data always pay their suppliers, the uncertainty is about the timing of the payment, and $\rho_j(\tau)$ reflects the cost of waiting to be paid rather than a premium for default risk.

cost of whichever source of funds the firm uses at the margin.[13]

The firm is risk neutral and chooses its bid before the delay is realized. If it wins and is paid after τ periods, the payment is worth $b/(1+\rho_j(\tau))$ at delivery. Its expected payoff from bidding b is

$$\pi(b; c_{j,ikt}) = \mathbf{P}_{j,ikt}(b) \left(\sum_{\tau \in \mathcal{T}} s_{it}(\tau) \left(\frac{b}{1+\rho_j(\tau)} \right) - c_{j,ikt} \right) = \mathbf{P}_{j,ikt}(b) \left(\frac{b}{1+r_{j,it}} - c_{j,ikt} \right), \tag{3}$$

where $\mathbf{P}_{j,ikt}(b)$ is the probability of winning with bid b, and the second equality defines the *financing wedge* $r_{j,it}$ as

$$\frac{1}{1+r_{j,it}} \equiv \sum_{\tau \in \mathcal{T}} \frac{s_{it}(\tau)}{1+\rho_j(\tau)}. \tag{4}$$

The wedge $r_{j,it}$ collapses the buyer's delay distribution and the firm's cost of liquidity into a single rate.[14] It varies across firms through $\rho_j(\cdot)$, and across buyers and over time through $s_{it}(\cdot)$. We assume it does not vary with the size of the contract, so $r_{j,it}$ is the same for every cost draw and factors out of the bidding and entry problems below.

4.3 Bidding

Conditional on entry, firm j observes $c_{j,ikt}$ and chooses its bid to maximize equation (3), which we rewrite as

$$\pi(b; c_{j,ikt}) = \frac{1}{1+r_{j,it}} \mathbf{P}_{j,ikt}(b) \left(b - \hat{c}_{j,ikt}\right), \qquad \hat{c}_{j,ikt} \equiv c_{j,ikt} \left(1+r_{j,it}\right), \tag{5}$$

where $\hat{c}_{j,ikt}$ is the *effective cost* of executing the contract: the production cost inflated by the cost of financing the payment delay. Because the outer factor $1/(1+r_{j,it})$ does not affect the optimal bid, the bidding problem is equivalent to a first-score auction in which the firm's private cost is $\hat{c}_{j,ikt}$ (Asker and Cantillon, 2008). The optimal bid $b^*_{j,ikt}$ satisfies the first-order condition

$$\left(b^*_{j,ikt} - \hat{c}_{j,ikt}\right) \mathbf{P}'_{j,ikt}\left(b^*_{j,ikt}\right) + \mathbf{P}_{j,ikt}\left(b^*_{j,ikt}\right) = 0. \tag{6}$$

Following Guerre et al. (2000), equation (6) can be inverted to recover the effective cost that rationalizes each observed bid:

$$\hat{c}_{j,ikt} = b^*_{j,ikt} + \frac{\mathbf{P}_{j,ikt}\left(b^*_{j,ikt}\right)}{\mathbf{P}'_{j,ikt}\left(b^*_{j,ikt}\right)}. \tag{7}$$

The inversion identifies the distribution of effective costs $F_{\hat{c},j,ikt}$, not the distribution of production costs $F_{c,j,ikt}$. The two coincide only when payment delays are costless ($r_{j,it} = 0$).

[13] Appendix D shows that if the firm combines external credit and internal funds, it equates their marginal costs at the optimum, which pins down $\rho_j(\tau)$. As a benchmark, with frictionless access to credit, $\rho_j(\tau)$ would be close to the risk-free rate over τ periods, which is common across firms and close to zero at the horizons we study. The excess of $\rho_j(\tau)$ over this hypothetical benchmark reflects the firm's *financial constraint*.

[14] The wedge is the s_{it}-weighted harmonic mean of the gross factors $1+\rho_j(\tau)$.

4.4 Entry

At the entry stage, firm j observes its entry cost $\kappa_{j,ikt}$ but not its production cost (Levin and Smith, 1994; Li and Zheng, 2009; Hubbard and Paarsch, 2016). It enters if the entry cost does not exceed its expected payoff from entering, $\Pi_{j,ikt}$, which averages the bidding payoff in equation (5) over cost draws. Because the financing wedge is the same for every cost draw, it factors out of this average:

$$E_{j,ikt} = 1 \iff \kappa_{j,ikt} \leq \Pi_{j,ikt} = \frac{\widehat{\Pi}_{j,ikt}}{1 + r_{j,it}}, \qquad \widehat{\Pi}_{j,ikt} \equiv \int \mathbf{P}_{j,ikt}\left(b^*_{j,ikt}(\hat{c})\right)\left(b^*_{j,ikt}(\hat{c}) - \hat{c}\right) dF_{\hat{c},j,ikt}(\hat{c}), \quad (8)$$

where $\widehat{\Pi}_{j,ikt}$ is the expected profit from bidding, measured at the payment date. Integrating over entry costs, firm j enters with probability

$$\phi_{j,ikt} = G_{\kappa,j,ikt}\left(\frac{\widehat{\Pi}_{j,ikt}}{1 + r_{j,it}}\right). \quad (9)$$

Equation (9) shows how payment delays affect entry. The wedge enters the payoff from entering in two places. First, it discounts the profit from bidding, which lowers the payoff of every firm with a positive cost of liquidity. Second, it shapes $\widehat{\Pi}_{j,ikt}$ itself through the effective costs of firm j and of its rivals, and through rivals' entry decisions. The sign of this second effect depends on market structure: a firm whose wedge is small relative to its rivals' may gain ground when delays are long and lose it when delays shorten. The net effect of payment delays on entry, and through entry on markups, is therefore an empirical question that we address with the estimated model.

Equilibrium. A Bayesian Nash equilibrium consists of entry rules and bid functions $\{E^*_{j,ikt}(\cdot), b^*_{j,ikt}(\cdot)\}_{j \in \mathcal{J}_{ikt}}$ such that, for every potential bidder: (i) conditional on entry, $b^*_{j,ikt}(\cdot)$ satisfies equation (6) given rivals' entry probabilities and bid functions; and (ii) firms enter according to equation (8), given the expected profit implied by these bid functions. Entry and bidding are jointly determined, as $\widehat{\Pi}_{j,ikt}$ integrates over the (equilibrium) bid functions that govern bidding after entry.

Discussion. The model delivers three objects that we recover in Section 5. First, observed bids identify the distribution of effective costs through equation (7). Second, because the effective cost is the product of the production cost and the financing wedge, the reform-induced changes in buyers' delay distributions $s_{it}(\cdot)$ separate the wedge $r_{j,it}$—and the underlying cost of liquidity $\rho_j(\cdot)$—from production costs. Third, given the recovered wedge and expected profits, observed entry decisions identify the distribution of entry costs through equation (9). With these primitives, we can quantify how much of the price decline documented in Section 3 reflects lower financing costs and how much reflects tougher competition, and evaluate counterfactual payment policies.

5 Model Estimation

We estimate the model on the pharmaceutical auctions described in Section 2.2 in two steps. In the first step, we recover the distribution of effective costs from observed bids, without taking a stand on how effective costs split into production and financing costs. In the second step, we use the reform-induced changes in buyers' delay distributions to separate the financing wedge from production costs. Given the wedge and the distribution of effective costs, we then recover the distribution of entry costs from observed entry decisions. Appendix E provides further details on each step.

5.1 Effective Costs

The inversion in equation (7) requires each bidder's probability of winning, $\mathbf{P}_{j,ikt}(\cdot)$, and its derivative. This probability depends on which rivals enter, what they bid, and their non-price attributes. We estimate each of these objects separately and combine them by simulation.

Entry probabilities. We predict the probability that each potential bidder enters the auction, $\hat{\phi}_{j,ikt}$, with a gradient-boosted classifier (Friedman, 2001; Ke et al., 2017). The predictors include firm characteristics, auction characteristics, and the buyer's payment probabilities. We use a flexible classifier because the goal of this step is prediction: the entry probabilities summarize the competition each bidder expects, and we do not interpret the predictors structurally.

Bids and non-price attributes. We predict each potential bidder's log price bid with a linear regression on firm and auction characteristics, the buyer's payment-delay distribution, and product and buyer-by-year fixed effects, estimated on observed bids. The residuals capture the dispersion in bids driven by bidders' private costs, and we allow their scale to vary across products. We predict each non-price attribute with a fractional logit (Papke and Wooldridge, 1996) on the firm's, buyer's, and product's average past scores, the scoring weights, and firm size. Both models deliver predictions for every potential bidder, including firms that do not enter.

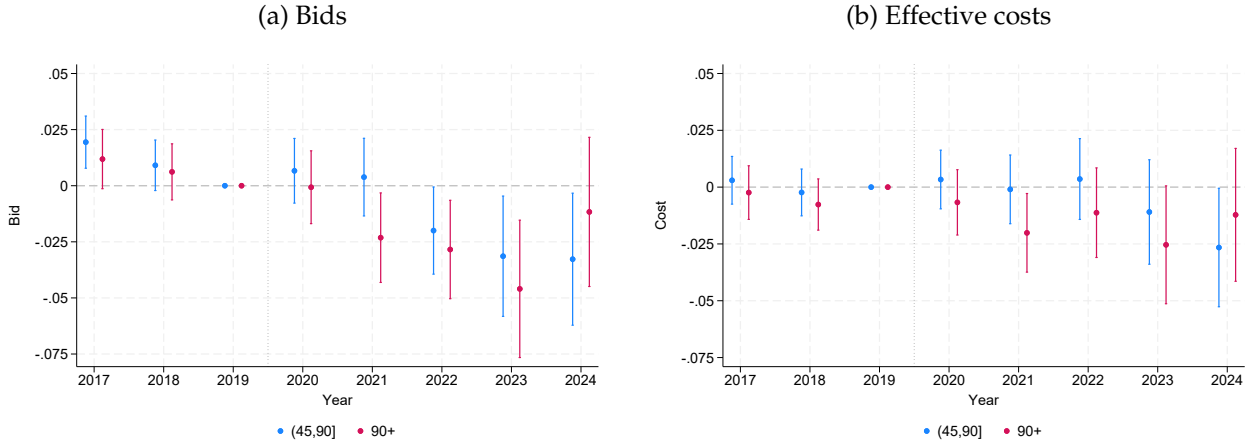
Winning probabilities and cost inversion. For each auction, we simulate rivals' entry from $\hat{\phi}$, their bids from the predicted bids and resampled residuals, and their non-price attributes from the fractional-logit predictions. The share of simulated auctions in which bidder j obtains the highest score with bid b estimates $\mathbf{P}_{j,ikt}(b)$, and a local regression of this share on b estimates its derivative. We use the same simulation draws for all bidders and bids within an auction, which reduces simulation noise in the derivative (Glasserman, 2003). Substituting these estimates into equation (7) yields the effective cost $\hat{c}_{j,ikt}$ of each observed bid, as in the inversion of first-price

auctions with asymmetric bidders (Guerre et al., 2000; Campo et al., 2003) and its extension to auctions in which non-price attributes affect the allocation (Buchholz et al., 2025).[15]

The inversion is computationally demanding. The rival panel is defined at the level of potential bidder and auction, about 3.7 million pairs in 145,000 auctions, and each auction requires 1,000 simulation draws that we evaluate at several bids for every entrant. The scale and richness of the data, however, are what make this approach informative: we recover effective costs for more than 600,000 bids, each against rivals whose entry, prices, and non-price attributes vary with the characteristics of the specific auction.

Changes in bids and effective costs. The inverted costs give a first look at how the reform affected suppliers' costs, before we impose any structure on the financing wedge. Figure 6 applies the difference-in-differences specification in equation (1) to bids and inverted effective costs. Neither outcome shows differential trends before the reform. After the reform, both fall in auctions held by late payers relative to early payers. Appendix Table B.8 reports the static version and the implied change in markups. In auctions held by severe late payers, bids fell by 2.8 percent of the product's median bid and effective costs by 1.9 percent, so about 70 percent of the decline in bids reflects lower effective costs and the rest lower markups. In auctions held by moderate late payers, bids fell by 2.5 percent, mostly through lower markups. The decline in effective costs is consistent with a lower financing wedge, but it could also reflect changes in production costs. Section 5.2 separates the two.

Figure 6: Effect of the reform on bids and effective costs



Notes: Estimates of $\gamma_{g\tau}$ from equation (1) at the bid level, with 95% confidence intervals. The outcomes are the observed bid (panel a) and the effective cost recovered from equation (7) (panel b), both divided by the median bid for the product. Pharmaceutical auctions, bids with a well-defined inversion. Buyer-by-product, firm, year, procedure-type, and quarter fixed effects, and log quantity; standard errors clustered by buyer-product-year.

[15] We drop bids for which the inversion is not well defined: bids with a simulated winning probability close to zero, a non-negative derivative, or a negative implied cost.

5.2 Separating the Financing Wedge from Production Costs

Inverted bids identify the effective cost $\hat{c}_{j,ikt} = c_{j,ikt}(1 + r_{j,it})$ but not its two components separately. Taking logs and using equation (4),

$$\log \hat{c}_{j,ikt} = \log c_{j,ikt} - \log \Big(\sum_{\tau \in \mathcal{T}} \frac{s_{it}(\tau)}{1 + \rho_j(\tau)} \Big). \tag{10}$$

We parametrize the cost of liquidity and the production cost as

$$\log \big(1 + \rho_j(\tau)\big) = \alpha_\tau + \mathbf{z}'_{jt}\theta_\tau, \qquad \log c_{j,ikt} = \mathbf{x}'_{j,ikt}\beta + \omega_j + \varepsilon_{j,ikt}, \tag{11}$$

where α_τ is the log financing factor at horizon τ, θ_τ lets it vary with firm characteristics $\mathbf{z}_{jt}$, $\mathbf{x}_{j,ikt}$ includes buyer, product, and time fixed effects and auction characteristics, ω_j is a firm fixed effect, and $\varepsilon_{j,ikt}$ is an unobserved cost shock. We group delays into four bins and normalize the cost of liquidity in the shortest bin to zero, so $\rho_j(\tau)$ measures the cost of waiting relative to prompt payment. The specification does not restrict how the cost of liquidity grows with the delay. It nests a constant monthly rate, $1 + \rho_j(\tau) = (1 + \rho_j)^{\tau - 1}$, in which α_τ is linear in τ. Substituting equation (11) into equation (10) gives the estimating equation

$$\log \hat{c}_{j,ikt} = \mathbf{x}'_{j,ikt}\beta + \omega_j - \log \Big(\sum_{\tau \in \mathcal{T}} s_{it}(\tau) \exp\big(-\alpha_\tau - \mathbf{z}'_{jt}\theta_\tau \big) \Big) + \varepsilon_{j,ikt}, \tag{12}$$

where $s_{it}(\cdot)$ is the empirical distribution of buyer i's payment delays at time t.

Identification. The fixed effects absorb permanent differences in costs across buyers, products, and firms, as well as common shocks over time. The wedge is therefore identified from changes in a buyer's delay distribution over time. The reform provides these changes: it shortened delays by different amounts across buyers, depending on their pre-reform payment behavior (Section 3). The identifying assumption is the same as in the difference-in-differences analysis of Section 3: absent the reform, production costs would have evolved in parallel across buyers with different pre-reform delays. Formally, conditional on the fixed effects, changes in $s_{it}(\cdot)$ are unrelated to the cost shocks $\varepsilon_{j,ikt}$. Under this assumption, the decline in effective costs in Figure 6 reflects a lower financing wedge, and equation (12) uses this variation to recover the cost of liquidity. Because the reform changed the whole delay distribution, and not only its mean, it also separates the cost of liquidity across delay horizons.

Estimation. Equation (12) is linear in (β, ω_j) and nonlinear in $(\alpha_\tau, \theta_\tau)$. We estimate it by nonlinear least squares, concentrating out the fixed effects, and cluster standard errors by buyer and year. We estimate the equation separately for small and large firms. The estimates give the wedge $\hat{r}_{j,it}$

through equation (4) and the production cost of each bid as $\log \hat{c}_{j,ikt} - \log(1 + \hat{r}_{j,it})$.

5.3 Entry Costs

Equation (9) relates each potential bidder's entry probability to its expected profit from bidding. We compute $\widehat{\Pi}_{j,ikt}$ for every potential bidder by simulation. We draw effective costs from their distribution conditional on firm and auction characteristics, which we obtain by projecting the inverted costs on these characteristics. For each draw, we compute the optimal bid against the same simulated rivals as in Section 5.1 and average the resulting profits.

We assume that entry costs are lognormal (Athey et al., 2011; Krasnokutskaya and Seim, 2011), $\log \kappa_{j,ikt} \sim N(\mathbf{w}'_{j,ikt}\gamma, \sigma^2)$, where $\mathbf{w}_{j,ikt}$ includes firm size, quantity, and the location of the firm relative to the buyer. Equation (9) then becomes

$$\phi_{j,ikt} = \Phi\Big(\frac{1}{\sigma}\big(\log \widehat{\Pi}_{j,ikt} - \log\left(1 + r_{j,it}\right) - \mathbf{w}'_{j,ikt}\gamma\big)\Big), \tag{13}$$

where Φ is the standard normal distribution function. We replace $\phi_{j,ikt}$ with $\hat{\phi}_{j,ikt}$ and $r_{j,it}$ with $\hat{r}_{j,it}$, which enters with the same coefficient as $\log \widehat{\Pi}_{j,ikt}$, and add buyer, product, and year fixed effects. Expected profits are measured with error and are jointly determined with rivals' entry, both of which bias the coefficient on $\log \widehat{\Pi}_{j,ikt}$ toward zero. We therefore instrument expected profits with the log number of potential bidders in the auction, which shifts the competition a bidder expects but, conditional on the fixed effects and $\mathbf{w}_{j,ikt}$, is unrelated to its entry cost. Standard errors are clustered by buyer.

5.4 Estimation Results

Table 1 reports the main parameters. We summarize the cost of liquidity with the constant-monthly-rate version of equation (11).

Effective costs and markups. The inversion implies substantial markups over effective costs. The median markup, as a share of the bid, is 20 percent for small firms and 25 percent for large firms.

Cost of liquidity. Firms' marginal cost of liquidity is 0.87 percent per month, or 11 percent per year. It differs markedly by firm size: small firms face 0.99 percent per month (12.5 percent per year), and large firms 0.44 percent (5.4 percent per year), an estimate that is not statistically different from zero. Appendix Table E.4 reports alternative specifications of the term structure. When we let the cost of liquidity vary freely across delay bins, or add a quadratic term in the delay, the point estimates for small firms increase more than proportionally with the delay, whereas those for large firms are flat, although the curvature is imprecisely estimated. The estimates are robust to how we

measure firm size and to heterogeneity by contract size (Appendix E.4). Splitting firms by their registered status as micro, small, or medium enterprises instead of by sales gives similar rates, and the estimated wedge does not vary systematically with the size of the contract relative to the firm's sales, consistent with the assumption in Section 4.2. Appendix Figure A.7 shows how the reform changed the implied financing wedge in auctions held by buyers with average delays above 45 days before the reform. In 2019, the wedge was 1.3 percent of production costs for small firms and 0.5 percent for large firms. It fell by half in 2020, the year of the rollout, and to nearly zero for both groups in 2021 and 2022. It rose again in 2023, when automatic payments were interrupted.

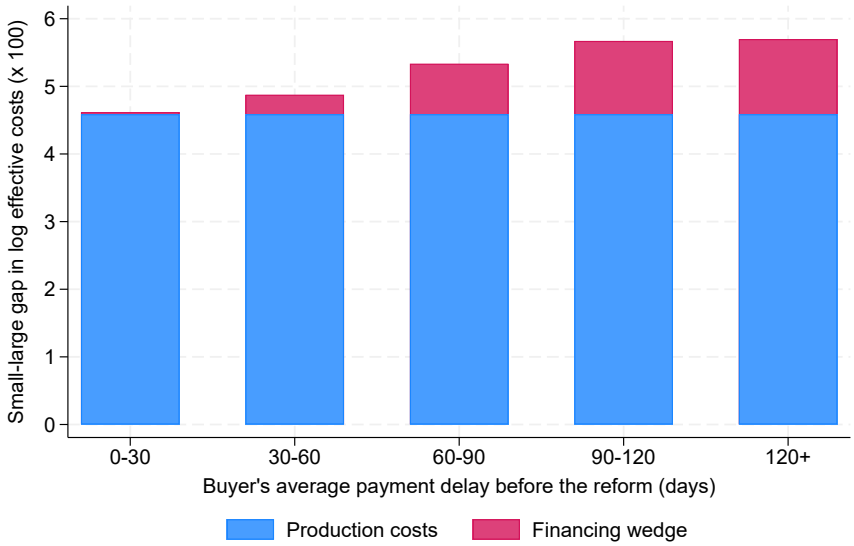
Production costs. Panel B of Table 1 describes the firm and buyer fixed effects in the production cost, ω_j and the buyer component of $\mathbf{x}'_{j,ikt}\beta$. Small firms have 4.6 log points higher firm fixed effects on average. Production costs are, however, dispersed within each group.[16] Production costs also vary across buyers: for the same product and firm, serving the buyer at the 90th percentile of the distribution of buyer effects costs about 26 percent more than serving the buyer at the 10th percentile. Most buyer effects lie within 20 log points of the mean, with a long left tail of a few buyers that are substantially cheaper to serve (Appendix Figure A.6). Some buyers are therefore more costly to serve, for instance because of their location, or their delivery requirements. This is consistent with the large differences in the prices that public buyers pay for the same products documented by Bandiera et al. (2009) and, in Chilean pharmaceutical procurement, by Allende et al. (2024) and Allende et al. (2025).

Cost asymmetries. Payment delays widen the cost gap between small and large firms. Figure 7 decomposes the small-large difference in log effective costs into production costs and financing wedges, by the buyer's pre-reform payment delay. Small firms have production costs about 5 percent higher than large firms. The financing wedge adds to this gap in proportion to the buyer's delays: it is negligible for buyers that pay within 30 days, 0.7 percentage points for those that pay within 60 to 90 days, and about 1.1 percentage points for those that pay after more than 90 days, about a fifth of the total gap.

Entry costs. Conditional on expected profits, quantity, and location, large firms have higher entry costs than small firms: the expected entry cost is 9.9 percent of the product's median bid for large firms and 6.4 percent for small firms. Small firms therefore face higher production and financing costs once they bid, but enter more easily. The coefficients on the controls, which we do not report in Table 1, are also informative. Entry costs increase less than proportionally with the size of the contract: conditional on the product fixed effects, their elasticity with respect to quantity is about

[16] This dispersion is larger among small firms than among large firms, with standard deviations of 0.39 and 0.27 log points. Appendix Figure A.5 shows the two distributions: the firm effects of large firms are concentrated around the mean, whereas those of small firms spread over a wider range of both low- and high-cost firms.

Figure 7: Cost gap between small and large firms, by buyer payment delay



Notes: Difference in log effective costs between small and large firms (multiplied by 100), decomposed into the difference in log production costs and the difference in log financing wedges, $\log(1+\hat{r}_{j,it})$, by the buyer's average payment delay in 2019. Neither component is weighted by participation. The production-cost gap is the difference in mean firm effects $\hat{\omega}_j$ between small and large firms, with one observation per firm, and is the same in every delay bin. The wedge gap is computed for each buyer as the difference between the financing wedge of a small and of a large firm at the buyer's 2019 distribution of payment delays, and averaged across the buyers in each delay bin, with one observation per buyer. Small firms have annual sales below 17 million USD.

-0.11, so they are a smaller share of larger contracts. The estimated dispersion of log entry costs is $\hat{\sigma} = 0.78$.

Table 1: Estimated parameters

	All firms	Small firms	Large firms
Panel A. Cost of liquidity			
Monthly rate, $\log(1+\rho)$	0.0087	0.0098	0.0044
	(0.0048)	(0.0049)	(0.0060)
Annualized rate	11.0%	12.5%	5.4%
Observations	587,293		
Panel B. Production costs			
Firm effects, ω_j: mean	0.000	0.010	-0.036
Standard deviation	0.368	0.391	0.270
Buyer effects: standard deviation	0.118		
90th–10th percentile	0.231		
Residual standard deviation	0.551		
Panel C. Entry costs			
Dispersion of log entry cost, σ	0.777		
	(0.037)		
Fixed effects in γ, standard deviation:			
Buyer	0.514		
Product	0.740		
Expected entry cost / median bid	0.073	0.064	0.099
Observations	2,692,777		

Notes: Panel A reports estimates of equation (12) under a constant monthly rate, $\log(1+\rho_j(\tau)) = \log(1+\rho_j)\,(\tau-1)$, estimated separately for small firms (annual sales below 17 million USD) and large firms; the annualized rate is $(1+\hat{\rho})^{12}-1$. Standard errors clustered by buyer and year. Panel B describes the firm and buyer fixed effects in the log production cost, $\log \hat{c}_{j,ikt} - \log(1+\hat{r}_{j,it})$, estimated jointly with product, year, month, and procedure-type fixed effects and log contract value; firms and buyers with at least 10 bids (202 firms and 187 buyers), unweighted. Firm effects are normalized to have mean zero across firms. Panel C reports instrumental-variables estimates of equation (13), instrumenting expected profits with the log number of potential bidders. The specification includes buyer, product, and year fixed effects, but not firm fixed effects, and controls for firm size, log quantity, and the location of the firm relative to the buyer. The standard deviations of the buyer (187 buyers) and product (1,077 products) fixed effects are in log entry-cost units and unweighted across buyers or products. The expected entry cost is evaluated at the median potential bidder of each group, as a share of the median bid for the product. Standard errors clustered by buyer.

6 Counterfactual Analysis

We use the estimated model to separate the channels through which payment delays affect procurement outcomes. Shorter delays lower the effective cost of executing a contract, which firms pass through to their bids. They also change the payoff from entering an auction, and with it the set of firms that compete and the markups they charge. Because the cost of liquidity is higher for small firms, both channels operate asymmetrically across firm sizes. The reduced-form estimates in Section 3 capture the combined effect of these channels; the model allows us to quantify each of them separately.

6.1 Simulation Design

Sample. We simulate equilibrium outcomes for a sample of 100 pharmaceutical auctions held in 2019, the last year before the reform.[17] To focus on auctions in which payment delays are costly, we draw the sample from auctions held by late payers. To select the set of auctions, we stratify the draw by buyer and by quartile of the quantity purchased, and include at most eight auctions per buyer. The resulting sample covers 14 buyers with an average payment delay of 106 days, and the average auction has 16.8 potential bidders, two thirds of them small firms. In ongoing work, we are extending the exercise to a larger and more representative set of auctions, buyers, and years, to provide a more comprehensive picture.

Baseline. For each auction, we solve for the Bayesian Nash equilibrium of the entry and bidding game in Section 4 using the estimated primitives: the distributions of production costs and non-price attributes of each potential bidder, the financing wedges $r_{j,it}$ implied by the buyer's 2019 delay probability distribution and the cost of liquidity of the firm's size group, the distribution of entry costs, and the buyer's scoring rule. Given entry probabilities, we compute equilibrium bid functions by letting each firm re-optimize its bid on a grid against simulated rivals, as in Buchholz et al. (2025); given bid functions, we update entry probabilities through equation (9); and we iterate until entry probabilities stabilize.[18] In this baseline, the median financing wedge is 1.9 percent for small firms and 0.8 percent for large firms.

Counterfactual scenarios. We eliminate the cost of financing payment delays, $r_{j,it} = 0$, in three steps that progressively let the market equilibrium respond:

[17] Solving for the equilibrium of the entry and bidding game is computationally intensive: for each auction and scenario, it requires iterating between the bidding equilibrium and the entry fixed point, simulating expected profits and winning probabilities at every step. For this reason, we currently restrict the exercise to a small sample of auctions.

[18] We evaluate expected profits and winning probabilities by simulation, with 500 draws of rivals' entry decisions, costs, and non-price attributes per auction. All scenarios use the same draws, so differences across scenarios do not reflect simulation noise in the draws themselves (Glasserman, 2003). We dampen the updates of bid functions and entry probabilities to stabilize the fixed point.

1. *Bids, entry fixed.* We remove the financing wedge from firms' bidding problems, so that bids reflect production costs rather than effective costs, and hold entry probabilities at their baseline values. This scenario isolates the pass-through of lower financing costs to bids, together with firms' strategic responses to their rivals' lower bids.

2. *Bids and entry response.* We also let entry probabilities respond to the new expected profits from bidding, $\widehat{\Pi}_{j,ikt}$ in equation (9), while keeping the baseline wedge in the denominator, $1 + r_{j,it}$. The difference with scenario 1 captures how the change in the competitive environment, which favors small firms, reshapes entry.

3. *Full elimination.* We also set $r_{j,it} = 0$ in the denominator of equation (9). The difference with scenario 2 captures the direct effect of financing costs on the value of entering.

Scenarios 1 and 3 bound the effects of eliminating financing costs with and without an entry response; scenario 2 decomposes the entry response into its two sources in equation (9).

6.2 Decomposing the Effects of Financing Costs

Table 2 reports the results. Firm-level outcomes weight each potential bidder by its baseline entry probability, so that they reflect the firms most likely to participate: changes in entry probabilities are weighted means, consistent with the expected number of entrants in Panel B, and changes in bids are weighted medians. Auction-level outcomes are medians across auctions.

Pass-through of financing costs. Scenario (1) shows how lower financing costs reach bids. Holding entry fixed, eliminating the wedge lowers the median bid by 1.7 percent for small firms and by 1.2 percent for large firms, and the median winning bid by 1.5 percent. Two features of these responses are worth noting. First, small firms pass through most, but not all, of their lower costs: their bids fall by 1.7 percent, compared with a wedge of 1.9 percent. Second, large firms lower their bids by more than their own wedge of 0.8 percent. Since they face a smaller reduction in costs, the rest of their response reflects competitive pressure: their small rivals, whose costs fall the most, become more aggressive, and large firms respond by reducing their markups. Lower financing costs therefore make the cost distributions of small and large firms more similar, and small firms win more often, with their share among winners rising from 63.6 to 64.0 percent.

Entry response. Scenarios (2) and (3) let entry respond. When expected profits adjust, in scenario (2), entry falls for both groups, but much more for large firms: their entry probability declines by 2.2 percentage points, compared with 0.5 percentage points for small firms, and about three quarters of large potential bidders enter less often. As the bids of their small rivals fall, large firms expect to win less often and to earn lower margins when they do, consistent with the evidence

Table 2: Counterfactual decomposition of the effects of financing costs

	Baseline 2019	(1) Bids, entry fixed	(2) Bids and entry response	(3) Full elimination
Panel A. Firm level				
Financing wedge, $\log(1 + r_{j,it})$				
Small firms	0.019	0	0	0
Large firms	0.008	0	0	0
Δ Entry probability (p.p.)				
Small firms		0	−0.5	−0.3
Large firms		0	−2.2	−2.2
Δ Log median bid (%)				
Small firms		−1.7	−1.3	−1.6
Large firms		−1.2	−0.8	−1.2
Panel B. Auction level				
Expected entrants, small firms	3.08	3.08	2.99	3.00
Expected entrants, large firms	1.56	1.56	1.46	1.45
Share of small firms among winners (%)	63.6	64.0	64.9	64.4
Δ Log winning bid (%)		−1.5	−1.1	−1.4

Notes: Simulated equilibrium outcomes for 100 pharmaceutical auctions held in 2019 by late payer buyers. The baseline solves the entry and bidding equilibrium with the estimated primitives and 2019 financing wedges. Scenario (1) sets $r_{j,it} = 0$ in the bidding problem and holds entry probabilities at their baseline values; scenario (2) also lets entry probabilities respond to expected profits, discounted by the baseline wedge; scenario (3) sets $r_{j,it} = 0$ in both the bidding problem and the payoff from entering. Changes are relative to the baseline. Panel A weights potential bidders by their baseline entry probabilities: changes in entry probabilities are weighted means and changes in bids are weighted medians; the baseline wedge is the unweighted median. Small firms have annual sales below 17 million USD. In Panel B, expected entrants are averages across auctions of the sum of entry probabilities; the share of small firms among winners and the change in the median simulated winning bid are medians across auctions.

that incumbent firms participate less when they anticipate fiercer competition (Carril et al., 2026). Small firms gain from a smaller cost disadvantage relative to large rivals, but also face fiercer competition from other small firms, and the two effects nearly offset. As a result, the expected number of entrants falls from 4.6 to 4.4 per auction, and the composition of entrants shifts toward small firms, whose share among expected entrants rises from 66.4 to 67.3 percent and whose share among winners rises to 64.9 percent. Fewer entrants soften competition, and the decline in the winning bid shrinks from 1.5 to 1.1 percent. Removing the wedge from the payoff from entering, in scenario (3), raises the value of entry most for small firms, whose decline in entry shrinks to 0.3 percentage points, and restores most of the price decline, to 1.4 percent.

Discussion. The decomposition highlights that payment delays shape procurement outcomes through two channels. Directly, they raise effective costs, and more so for small firms with a higher cost of liquidity, which firms pass through to bids. Indirectly, they shift the competitive balance between small and large firms, changing who enters and who wins. In our sample, the entry response partly offsets the direct effect on prices, since large firms withdraw as small firms gain ground, but it reinforces the shift of contracts toward small firms. Eliminating financing costs works like a bid preference for small firms, a common policy in public procurement (Marion, 2007; Krasnokutskaya and Seim, 2011; Athey et al., 2013), with a key difference: instead of distorting the award rule in their favor, it removes a friction that raises their costs.

The simulated price decline, of about 1.4 percent, is smaller than the reduced-form decline in winning bids of 4 to 6 percent for late payers in Section 3. The two exercises are not comparable: the counterfactual eliminates financing costs in a small sample of auctions held by 14 late payers in 2019, whose auctions are drawn by stratifying. The simulation sample was selected to represent auctions in which payment delays are costly, not the full population of auctions, so the simulated effects should be read as illustrative of the mechanisms rather than as aggregate effects of the reform.

7 Conclusion

This paper studies how payment delays shape competition in public procurement, using a reform that automated payments to suppliers of Chilean public health buyers within 30 days. We find that the cost of financing payment delays is substantial, that it falls hardest on small firms, and that it shapes not only the prices that buyers pay but also which firms enter and win procurement auctions.

The reform sharply reduced payment delays for buyers that used to pay late, by about 40 days for moderate late payers and by 60 to 75 days for severe late payers. Auctions held by these buyers attracted more offers, particularly from small firms, and were awarded at prices about 4 percent lower. To separate the channels behind these effects, we develop and estimate a model of entry

and bidding in scoring auctions in which payment delays act as a firm-specific financing wedge on costs. We estimate a marginal cost of liquidity of 0.9 percent per month, or 11 percent per year. It is substantially higher for small firms, at 12.5 percent per year, than for large firms, at 5.4 percent, and for small firms it increases with the length of the delay. Payment delays are therefore a source of cost asymmetry among bidders: small and large firms have similar production costs on average, but small firms bear a financing cost that grows with the buyer's payment delay and accounts for up to a fifth of the cost gap between the two groups.

Using the model, we decompose the effects of eliminating financing costs in a sample of auctions held by late payers. Holding entry fixed, firms pass most of their lower financing costs through to bids, and large firms also lower their markups in response to more aggressive small rivals; winning bids fall by 1.5 percent and small firms win more often. When entry responds, large firms withdraw from auctions much more than small firms, which partly offsets the price decline but reinforces the shift of contracts toward small firms. Payment terms thus affect procurement outcomes both directly, through costs, and indirectly, through the competitive balance between small and large firms.

Taken together, these results show that financial constraints represent a meaningful cost for firms, and that this cost shapes both firm behavior and market equilibrium. Financing costs affect the prices that firms bid and their decisions to enter procurement auctions. Because they fall disproportionately on small firms, they also widen cost asymmetries among bidders. Removing these costs makes markets more symmetric and more competitive, lowering the prices that public buyers pay and shifting contracts toward small firms.

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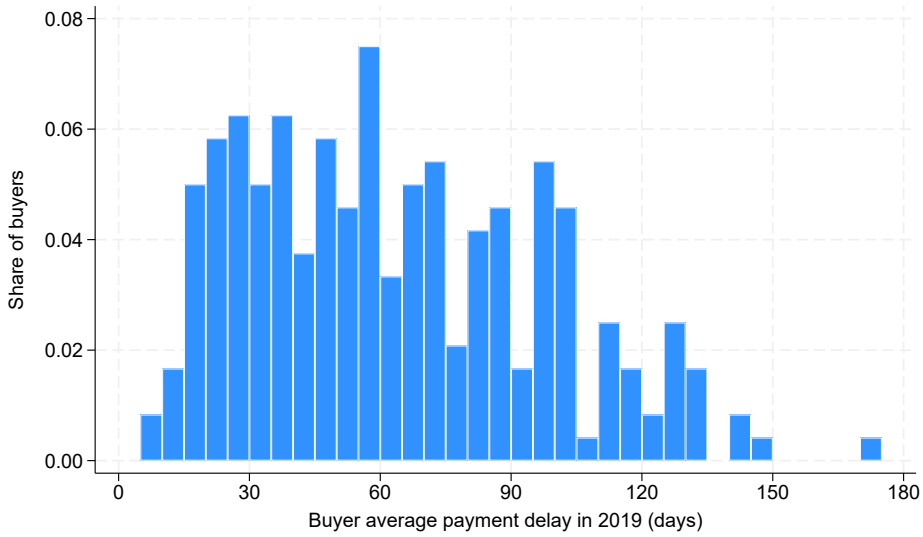
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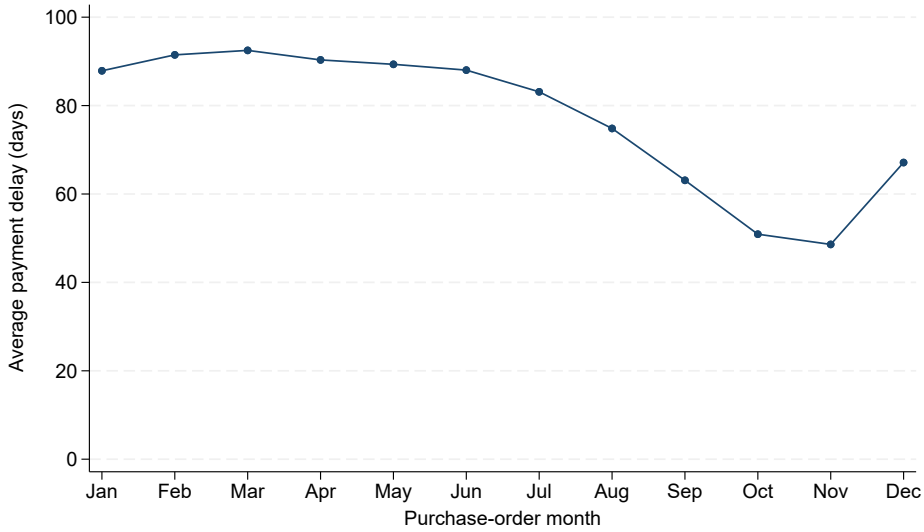
A Additional Figures

Figure A.1: Buyers' average payment delays before the reform, 2019



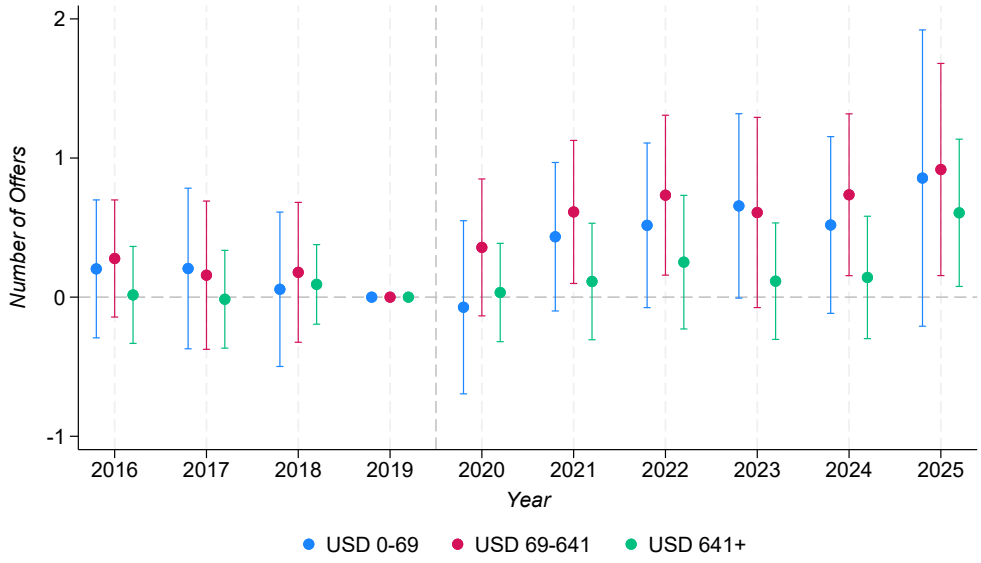
Notes: Distribution across public health buyers of the average payment delay—days between the acknowledgment of an invoice and its payment—of the invoices each buyer paid in 2019. One observation per buyer ($N = 242$). Bins of 5 days.

Figure A.2: Seasonality of payment delays



Notes: Average payment delay, in days, by month of issuance of the purchase order. Purchase orders issued in 2016–2019 and paid in 2016–2020, all public health buyers.

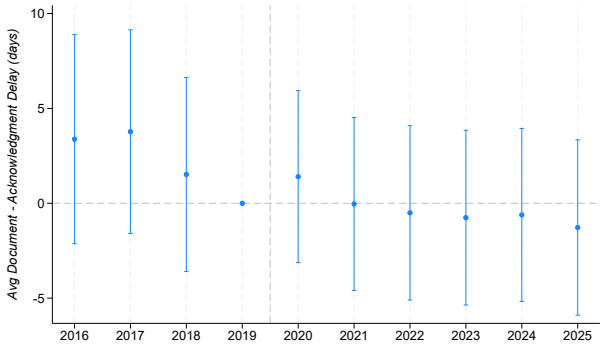
Figure A.3: Effect of the reform on the number of offers, by contract size



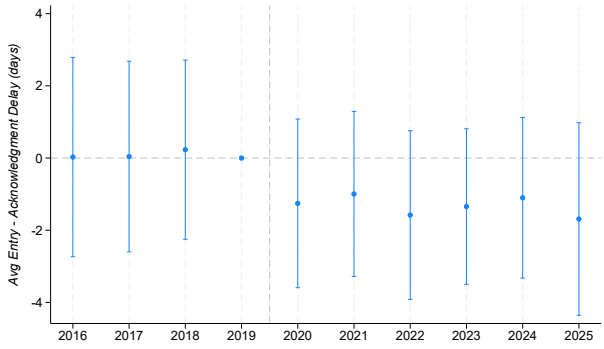
Notes: Triple-difference estimates of the effect of the reform on the number of offers per auction, by terciles of contract size. Late payers are buyers whose 2019 amount-weighted average payment delay exceeded 30 days. Buyer, year, procedure-type, and product (six-digit UNSPSC) fixed effects; standard errors clustered by buyer-year.

Figure A.4: Effect of the reform on invoice acknowledgment

(a) Days between purchase order and acknowledgment

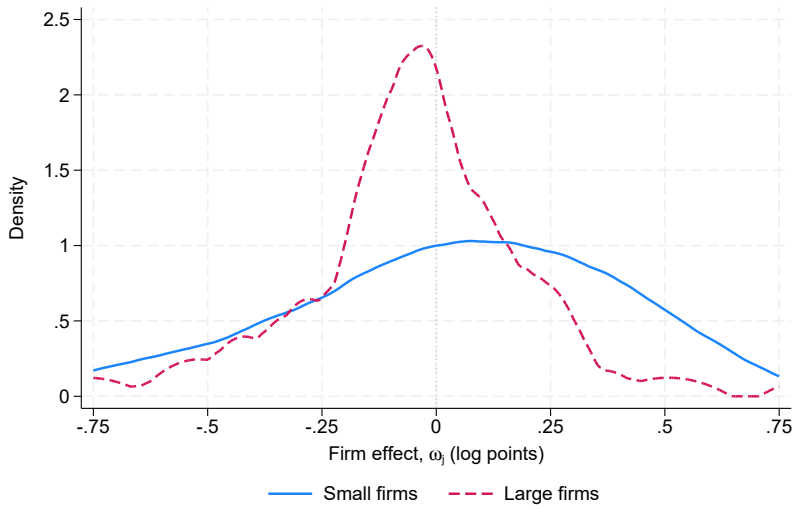


(b) Days between invoice entry and acknowledgment



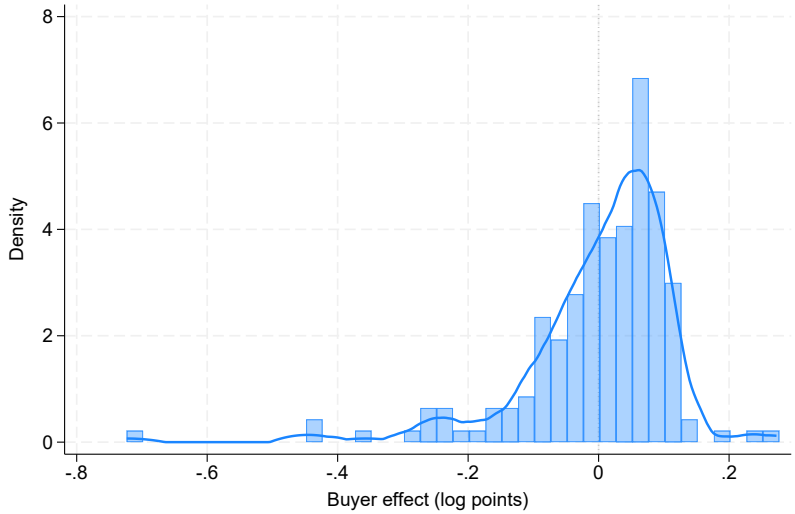
Notes: Estimates of the effect of the reform on the time buyers take to acknowledge the receipt of invoices, which starts the 30-day payment clock. Late payers are buyers whose 2019 amount-weighted average payment delay exceeded 30 days. Buyer and year fixed effects; standard errors clustered by buyer-year.

Figure A.5: Distribution of firm effects in production costs, by firm size



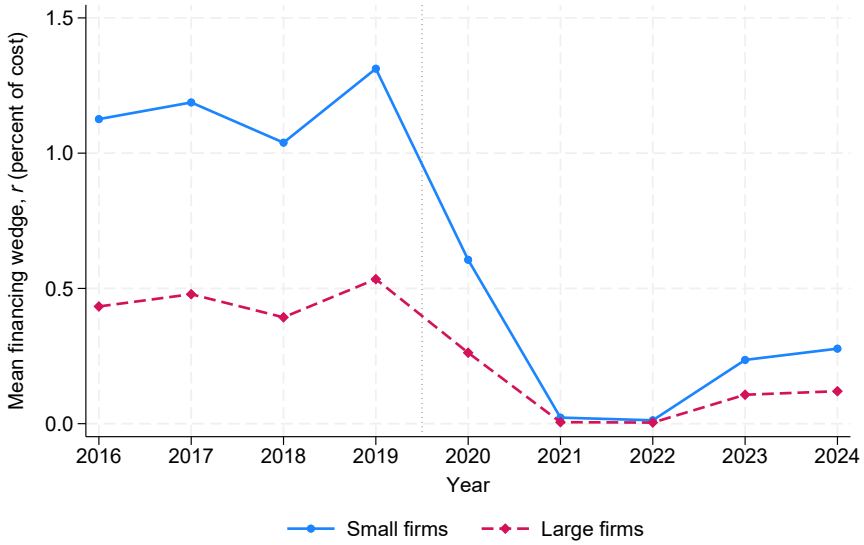
Notes: Kernel densities of the firm fixed effects ω_j in the log production cost, $\log \hat{c}_{j,ikt} - \log(1+\hat{r}_{j,it})$, estimated jointly with buyer, product, year, month, and procedure-type fixed effects and log contract value (Panel B of Table 1). Firms with at least 10 bids: 158 small and 44 large firms. Firm effects are normalized to have mean zero across firms. Densities are estimated on all firms and plotted between -0.75 and 0.75, a range that excludes 13 firms. Small firms have annual sales below 17 million USD.

Figure A.6: Distribution of buyer effects in production costs



Notes: Histogram and kernel density of the buyer fixed effects in the log production cost, from the same regression as Figure A.5. Buyers with at least 10 bids ($N = 187$). Buyer effects are normalized to have mean zero across buyers.

Figure A.7: Financing wedge in contracts of late-paying buyers, by firm size



Notes: Average estimated financing wedge $\hat{r}_{j,it}$, in percent of the production cost, across bids in auctions held by buyers whose average payment delay before the reform exceeded 45 days, by year and firm size. The wedge is computed from equation (4) with the estimates of equation (12) under a constant monthly rate, estimated separately for small and large firms, and the buyer's distribution of payment delays in each year. Bids with a well-defined inversion, excluding buyers that paid more than 20 percent of their invoices after 180 days. The dotted line marks the start of the reform. Small firms have annual sales below 17 million USD.

B Additional Tables

Table B.1: Characteristics of early and late payers, 2019

	Early Payer	Late Payer
N	40	167
Characteristics		
Avg Number of Beds	36	128
Avg Length of Stay (days)	8	11
Tenders		
Share of Goods	0.9	0.86
Avg Number of Bidders	4.21	3.7
Share of MSMEs Bidders	0.49	0.43
Share of MSMEs Awarded	0.43	0.37
Payments		
Avg. Transaction Size (CLP)	1,782,385	2,333,148
Avg. Weighted Delay (days)	22.39	78.55
Share of Delays $\leq$ 30 days	0.67	0.16
Share of Delays $\leq$ 45 days	0.84	0.27

Notes: Public health buyers classified by their 2019 average payment delay into early and late payers. Hospital characteristics (beds, length of stay) refer to hospitals; auction and payment statistics are averages across each group's 2019 auctions and invoices. MSMEs: micro, small, and medium enterprises.

Table B.2: What explains payment delays: sequential fixed-effects regressions

	Dependent variable: log(1 + payment delay in days)					
	(1)	(2)	(3)	(4)	(5)	(6)
	Scale	+ Month	+ Buyer	+ Supplier	+ Product	+ Interaction
Log purchase-order amount	0.030***	0.029***	-0.018**	0.010***	0.011***	0.009**
	(0.010)	(0.010)	(0.008)	(0.004)	(0.004)	(0.004)
Year-month FE	No	Yes	Yes	Yes	Yes	Yes
Buyer FE	No	No	Yes	Yes	Yes	Yes
Supplier FE	No	No	No	Yes	Yes	Yes
Product FE (8-digit)	No	No	No	No	Yes	Yes
Buyer x Supplier FE	No	No	No	No	No	Yes
Observations	1,113,551	1,113,551	1,113,551	1,113,551	1,113,551	1,088,005
R-squared	0.003	0.070	0.329	0.535	0.544	0.628
Adjusted R-squared	0.003	0.070	0.329	0.531	0.537	0.603

Standard errors two-way clustered by buyer and supplier.

Notes: Unit of observation: purchase order paid in 2016–2019, all public health buyers. Standard errors two-way clustered by buyer and supplier in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3: Firm-Level Summary Statistics

	Mean	Min	P10	P25	P50	P75	P90	Max
Firm age	12.02	0.00	2.00	4.00	10.00	21.00	25.00	31.00
Employees	92	0	1	2	8	33	150	9702
Annual sales (MM USD)	8.84	0.00	0.02	0.15	0.74	5.95	30.78	64.38
Natural person	0.07	0.00	0.00	0.00	0.00	0.00	0.00	1.00
In RM	0.73	0.00	0.00	0.00	1.00	1.00	1.00	1.00
Owned by another legal entity	0.49	0.00	0.00	0.00	0.00	1.00	1.00	1.00
Shr. public mkt.	0.29	0.00	0.00	0.00	0.15	0.54	0.84	1.00
Shr. health	0.14	0.00	0.00	0.00	0.02	0.20	0.47	1.00

Number of firms: 494

Notes: One observation per firm. The tax authority reports annual sales in 12 brackets, defined in UF (inflation-indexed units of account), rather than as exact amounts; we assign each firm the midpoint of its bracket (1.5 million UF for the open-ended top bracket, above 1 million UF) and convert it to USD. The number of employees is reported as a count. Missing years are linearly interpolated within firm. *Shr. public mkt.* is the value of purchase orders the firm received from all public buyers on Mercado Público in the previous year divided by its total sales in that year; *Shr. health* is the same ratio using only purchase orders from public health buyers. Both shares are capped at one. Ownership records from the tax authority are available for a subset of firms (89% of the firms in the sample); *Owned by another legal entity* is computed over this subset.

Table B.4: Entry and Bidding by Firm Size

	Firms	Obs	Entry Rate	Win Rate | Entry	Mean Log Bid | Entry	SD Log Bid | Entry
All	494	3,716,672	0.264	0.215	-0.000	0.591
Q1 (smallest)	148	143,956	0.102	0.067	0.194	0.738
Q2	144	620,696	0.178	0.064	0.066	0.618
Q3	99	776,081	0.186	0.141	0.033	0.612
Q4 (largest)	103	2,175,939	0.327	0.257	-0.021	0.577

Notes: Unit of observation: potential bidder × auction. Firms are grouped into quartiles of their annual sales as recorded in 2019 auctions (previous-year sales, imputed at the midpoint of the tax-authority sales bracket), computed across firms. For firms without a tax-authority sales record, we use their total sales on Mercado Público as a proxy; firms with neither (50 firms) are assigned the midpoint of the first tax-authority sales bracket. Quartile cutoffs: Q1 up to USD 0.06 million; Q2 above USD 0.06 million and up to 0.74 million; Q3 above USD 0.74 million and up to 6.37 million; Q4 above USD 6.37 million. Because sales are recorded in brackets, quartiles contain unequal numbers of firms. Entry rate: share of auctions in which a potential bidder submits a bid. Log bids are demeaned by product (ZGEN).

Table B.5: Auction-Level Summary Statistics

	Mean	Min	P10	P25	P50	P75	P90	Max
Potential bidders	30.17	8	14.00	20.00	29.00	38.00	47.00	76
Actual bids	4.65	1	1.00	2.00	4.00	6.00	9.00	22
Entry rate	0.16	0	0.06	0.10	0.15	0.21	0.27	1
Lowest bid wins	0.73	0	0.00	0.00	1.00	1.00	1.00	1
SD log bid (within auction)	0.43	0	0.12	0.20	0.33	0.56	0.85	13
Evaluation weights (share of total score)								
Weight: Price	0.50	0	0.30	0.40	0.50	0.60	0.70	1
Weight: Delivery	0.10	0	0.00	0.00	0.10	0.15	0.25	1
Weight: Technical	0.35	0	0.10	0.27	0.40	0.50	0.55	1
Weight: Other	0.04	0	0.00	0.00	0.00	0.05	0.15	1
Number of auctions: 211,660								

Table B.6: Non-price attributes: evaluation scores

Index	Mean	SD	Min	p25	Median	p75	Max
Technical	0.788	0.277	0.000	0.600	1.000	1.000	1.000
Delivery	0.912	0.223	0.000	1.000	1.000	1.000	1.000
Other	0.700	0.370	0.000	0.500	0.958	1.000	1.000

Notes: Scores received by bidders on each non-price dimension, normalized to $[0, 1]$, in pharmaceutical auctions held in 2016–2020 for which evaluation matrices were digitized.

Table B.7: Components of the technical score

Component	% of auctions	Avg. weight when included
Certificates	74.0	42.7
Bioequivalence	53.0	33.2
Experience	46.6	28.7
Pharmacovigilance	39.4	17.3
Presentation	28.1	19.8
Transportation	28.0	20.6
Exchange	24.0	21.6
Expiration	17.5	28.2
Formal requirements	17.4	20.8
Brand	9.5	18.3

Notes: Share of pharmaceutical auctions whose technical criterion includes each component, and its average weight within the technical score (in percent) when included. Certificates: e.g., GMP, FDA, EMA. Experience: years in the market and past contracts. Pharmacovigilance: drug monitoring and safety. Presentation: product format and size. Transportation: shipping and storage requirements. Exchange: replacement of expired or defective products. Expiration: days until expiration.

Table B.8: Effect of the reform on bids, effective costs, and markups

	Bid $b^*_{j,ikt}$	Effective cost $\hat{c}_{j,ikt}$	Markup $b^*_{j,ikt} - \hat{c}_{j,ikt}$
Post × moderate late payer	−0.0248	−0.0084	−0.0164
	(0.0077)	(0.0068)	(0.0036)
Post × severe late payer	−0.0275	−0.0194	−0.0081
	(0.0083)	(0.0072)	(0.0039)
Observations	546,928	546,928	546,928

Notes: Static version of equation (1) at the bid level. All outcomes are divided by the median bid for the product. Moderate (severe) late payers had an average payment delay of 45–90 (more than 90) days in 2019. Buyer-by-product, firm, year, and procedure-type fixed effects, and log quantity. Standard errors clustered by buyer-product in parentheses.

C The Payment Reform

This appendix describes the payment rules in place before the reform, the introduction of the reform, the incorporation of buyers into the new system, and its interruption in 2023.

Payment rules before the reform. Since a 2015 amendment to the regulation of the procurement law,[19] public buyers have been required to state payment terms in their tender documents and, as a general rule, to pay their suppliers within 30 calendar days of receiving the invoice; health-sector buyers may take up to 45 days. These rules, however, were not binding in practice. Each buyer paid its suppliers directly from its own accounts and no mechanism forced payment once the deadline had passed. The procurement agency, *ChileCompra*, has no oversight powers over buyers' payments, and sanctions required administrative investigations of individual officials by the Comptroller (*Contraloría General de la República*). ChileCompra's director attributed the delays mostly to "bureaucracy or negligence" rather than to a lack of funds, since buyers can only open a tender if the purchase is budgeted.[20,21]

Announcement. The commitment to pay suppliers on time was announced on March 19, 2020, as part of the Economic Emergency Plan in response to the COVID-19 pandemic. The announcement received broad press coverage. On April 6, 2020, the Minister of Finance, the Budget Director, and the Treasurer presented the centralized payment system under development; the Minister argued that, when the State is slow to pay, few firms can afford to participate in public procurement.[22]

The reform was implemented through administrative instructions issued by the Budget Office of the Ministry of Finance (*Dirección de Presupuestos*, DIPRES),[23] The latter states that the system pursues two direct objectives—ensuring compliance with the 30-day payment rule and improving the management of fiscal resources—and, indirectly, avoiding liquidity problems for suppliers, especially small and medium-sized ones.[24] Under the new system, known as the *Plataforma de Pagos Centralizados* (PPC), once a buyer acknowledges the reception of an invoice, the supplier is paid automatically 30 days later by the Treasury (*Tesorería General de la República*), and buyers must

[19] Article 79 bis of Decree 250 of 2004, which regulates Law 19,886

[20] See La Tercera, November 22, 2017.

[21] ChileCompra's efforts to curb late payments relied on complaints and on public pressure. Suppliers could file a complaint for late payment (*reclamo por pago no oportuno*) through Mercado Público, which ChileCompra forwarded to the buyer. ChileCompra published statistics and rankings of buyers by their complaint rate, ran a campaign for timely payment, and sent letters to the Comptroller identifying the buyers with the most complaints—49 letters in 2017, covering 177 institutions. Complaints nonetheless kept growing: they rose from 22,226 in 2016 to 35,356 in 2017, for a total of about USD 106 million. Four out of five complaints came from small firms, and the health sector accounted for 48% of the complaints and 55% of the amounts involved. Complaints covered less than 1% of purchase orders, far below the share of invoices paid late (Figure 1), which suggests that most suppliers did not use the mechanism.

[22] See ChileCompra, April 7, 2020.

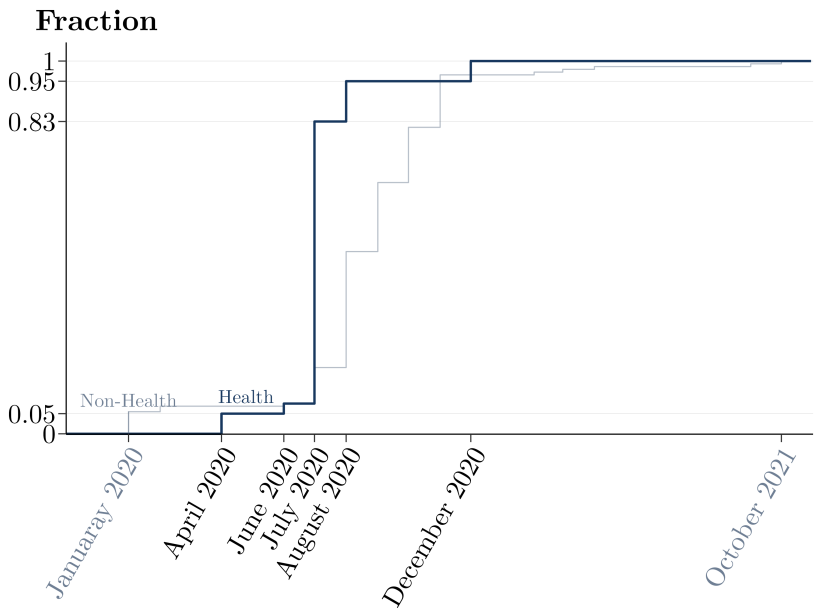
[23] Under the powers granted by the organic law of the State's financial administration (Decree Law 1,263 of 1975): Oficio Circular Nº8 and Nº9 of April 2020.

[24] See DIPRES, Oficio Circular Nº9, April 28, 2020.

abstain from paying those invoices themselves. Automatic payments applied to purchase orders issued after a buyer's incorporation.

Rollout. The instructions were announced for the whole central government at once: they covered all institutions included in the budget law except Congress, the Judiciary, and the Public Prosecutor's Office, and set May 1, 2020, as the start date for all institutions using the government's financial management system (SIGFE). In practice, however, buyers were incorporated in stages, following logistical criteria set by DIPRES rather than choices made by the buyers themselves—among them, each institution's adoption of the electronic reception of invoices during 2020. By September 2020, 319 ministries and public services, about 70% of the total, were operating under the new system.[25] Figure C.1 shows the share of buyers incorporated over time. A first group of non-health entities entered in January 2020. In the health sector, the first buyers entered in April 2020, and most of them entered together: 83% of health buyers had been incorporated by July 2020 and 95% by August 2020. The remaining health buyers entered in December 2020. The rollout in the rest of the central government was more gradual and was completed in October 2021.

Figure C.1: Rollout of automatic payments



Notes: The figure plots the cumulative share of buyers incorporated into the centralized payment platform by month, separately for buyers in the health sector (dark line) and for the rest of the central government (light line). Source: DIPRES.

[25] See Pauta, September 15, 2020.

Interruption in 2023. On March 8, 2023, DIPRES announced the temporary suspension of the platform after detecting duplicate payments.[26] From March 10, buyers had to pay their suppliers directly again. The suspension was initially announced for 180 days, but on April 19 DIPRES announced that the platform would resume operations on May 2, 2023. Buyers were reinstated gradually and only once they met a set of conditions—training of the staff operating the system, the signature of a compliance protocol, and the absence of pending refunds of duplicate payments. As of July 2024, only 5 of the 33 regional Health Services had been reinstated.

The interruption had two consequences for suppliers. First, buyers that were not reinstated returned to paying directly, which partially reversed the reduction in delays: the share of invoices paid within 30 days fell from 93% in 2021–2022 to 55% in 2023–2024 (Figure 1). Long delays, however, remained rare, and the average delay stayed well below its pre-reform level. Second, the interruption increased uncertainty about the timing of payments, which may affect participation decisions even when payments are ultimately made on time. Our analysis includes 2023 and 2024 data, so the estimated effects of the reform incorporate the interruption.

[26] See DIPRES, Oficio Circular N°14, March 8, 2023 (link). According to information provided by DIPRES, 15,862 duplicate disbursements were made between 2020 and August 2023, almost all of them in 2020, during the rollout. Of these, 8,475 corresponded to the health sector, of which about half had been refunded by suppliers by August 2023; the amount pending refund was about USD 10 million.

D The Marginal Cost of Liquidity

The winning firm pays $c_{j,ikt}$ at delivery and receives $b_{j,ikt}$ after a delay of τ periods. To finance this gap, it can combine external and internal funds. External sources—bank credit, factoring of the receivable, or supplier credit—carry a marginal cost $r^E_{jt}(\tau)$ that includes the interest rate and any default, collateral, or monitoring spread. Internal sources—cash reserves or retained earnings—carry a per-period shadow value λ_{jt}, which reflects forgone investment, other contracts, or a precautionary buffer. At the optimum, the firm equates the marginal cost of funds across the sources it uses:

$$\rho_j(\tau) = r^E_{jt}(\tau) = \lambda_{jt} \cdot \tau.$$

The marginal cost of liquidity $\rho_j(\tau)$ is therefore well defined regardless of which source finances the gap at the margin.

In a frictionless credit market with risk-free rate r_f, $\rho_j(\tau) = r_f \cdot \tau$, which is common across firms and close to zero at monthly horizons. Financial constraints drive $\rho_j(\tau)$ above this benchmark: limited access to external credit raises the spread embedded in $r^E_{jt}(\tau)$, and scarce internal funds raise λ_{jt} above r_f. Both forces are expected to be stronger for smaller, more levered, or less liquid firms, which therefore face a higher $\rho_j(\tau)$ that increases more steeply with the delay.

E Estimation Details

This appendix provides further details on each step of the estimation procedure in Section 5, in the order in which they are implemented: the set of potential bidders and their entry probabilities, the distributions of bids and non-price attributes, the inversion of bids, the cost of liquidity, and the distribution of entry costs.

E.1 Potential Bidders and Entry Probabilities

Classifier. We predict the probability that each potential bidder enters an auction with a gradient-boosted classifier (Friedman, 2001; Ke et al., 2017), trained on 6.4 million pairs of potential bidders and auctions, of which 15.4 percent enter. The predictors include the firm's lagged sales and employment, the share of its sales to public buyers, and its backlog of contracts and of unpaid receivables over the previous 180 days, both in the same product market and overall; the auction's scoring weights, procedure type, log quantity, and number of potential bidders; the product's therapeutic class and dosage form; the buyer's average payment delay; and the year and week of the auction. We replace the identifiers of buyers and products with smoothed averages of the entry rate by buyer-year and product-year, estimated within each training fold, and exclude all variables determined after bids are submitted. We tune the hyperparameters by Bayesian optimization (Akiba et al., 2019) and evaluate the classifier by five-fold cross-validation, grouping observations by auction so that no auction appears in both the training and the validation folds, and stratifying folds by year. Table E.1 reports the out-of-sample fit: the classifier separates entrants from non-entrants well, with an area under the ROC curve of 0.975, and the predicted probabilities are well calibrated (Figure E.1).

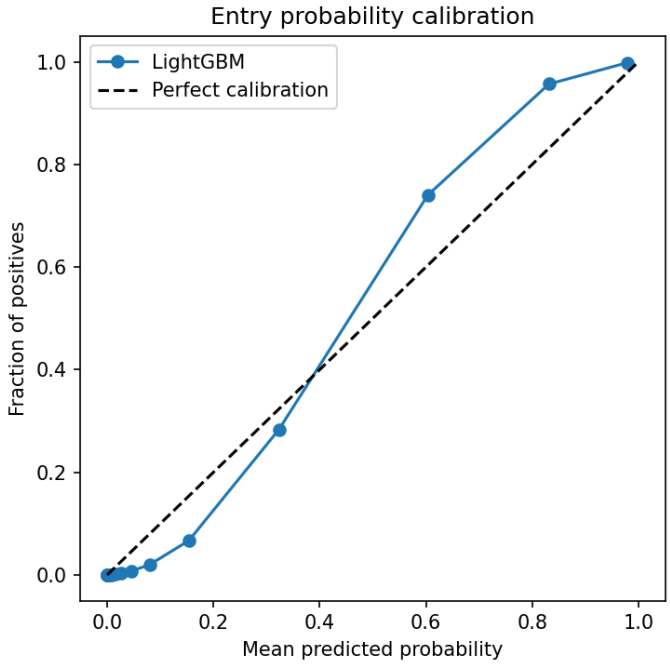
Restriction of the set of potential bidders. Many pairs of firms and auctions in the initial set of potential bidders have predicted entry probabilities close to zero: firms that are active in the product market and region but never bid for a given buyer's contracts. These pairs carry no information about entry costs and add to the computational burden of the simulations. We therefore drop the pairs whose average predicted entry probability across all auctions of the same buyer and product is below one percent. Because the rule is applied to an average over time rather than to the prediction for each auction, it does not depend on time-varying shocks such as the reform. Panel B of Table E.1 shows that the restriction drops 42 percent of the pairs but less than 0.1 percent of the observed entries, and reduces the median number of potential bidders per auction from 29 to 17.

Table E.1: Entry probabilities: model fit and set of potential bidders

Panel A. Out-of-sample fit (five-fold cross-validation)			
Area under the ROC curve	0.975		
Log-loss	0.144		
Brier score	0.044		
Pairs of potential bidders and auctions	6,385,661		
Entry rate	0.154		
Panel B. Restriction of the set of potential bidders			
	Before	After	Share kept
Pairs of potential bidders and auctions	6,385,661	3,716,672	58.2%
Observed entries	983,444	982,561	99.9%
Potential bidders per auction: mean	30.2	17.6	
Potential bidders per auction: median	29	17	

Notes: Panel A reports the average across the five validation folds; standard deviations across folds are below 0.0005. Folds are grouped by auction and stratified by year. Panel B drops pairs of firms and auctions whose average predicted entry probability across all auctions of the same buyer and product is below 0.01.

Figure E.1: Calibration of predicted entry probabilities



Notes: Average predicted entry probability and observed entry rate, by bins of the predicted probability. Pairs of potential bidders and auctions in pharmaceutical auctions, 2016–2025.

E.2 Bids and Non-Price Attributes

Bids. We regress the log price bid on firm and auction characteristics, the shares of the buyer's invoices paid after 30, 60, . . . , 210 days, and product and buyer-by-year fixed effects, on the roughly one million bids observed in the data. The firm characteristics include the firm's lagged sales, its backlog of contracts and receivables, whether it is located in the buyer's region, and the firm's average log bid relative to the product's average, which captures permanent differences in pricing across firms. The regression explains 96 percent of the variance of log bids, most of it through the product fixed effects. We use it to predict the bid of every potential bidder, including those that do not enter.

The residuals capture the dispersion of bids that is due to bidders' private costs. Their dispersion differs across products and increases with the level of prices, so we allow it to vary by product: for each product, we estimate the standard deviation of residuals and shrink it toward the average across products with an empirical Bayes estimator. Because most products have many bids, shrinkage is small: the shrinkage factor exceeds 0.1 for fewer than 8 percent of products. The median standard deviation is 0.40, with a 5th–95th percentile range of 0.22 to 0.73. To simulate rivals' bids, we draw standardized residuals from their empirical distribution, trimmed at the 2.5th and 97.5th percentiles, scale them by the product's standard deviation, and correct the level of simulated bids for the retransformation from logs (Duan, 1983).

As a robustness check, we predict bids with a gradient-boosted regression on the same predictors. It improves the fit only slightly (R^2 of 0.969 instead of 0.956), and the inverted costs are nearly identical (Table E.2).

Non-price attributes. We predict each of the three non-price attributes in the scoring rule—technical, delivery, and other—with a fractional logit (Papke and Wooldridge, 1996), estimated on the 45,945 bids for which evaluation scores are recorded. These scores come from the evaluation matrices of pharmaceutical auctions, which buyers publish as scanned documents and which were digitized by Allende et al. (2025). The predictors are the firm's, the buyer's, the product's, and the therapeutic class's average scores in each of the three dimensions, the scoring weights, the firm's lagged sales, and a log time trend. The McFadden pseudo-R^2 is 0.16 for technical scores, 0.24 for delivery scores, and 0.27 for other scores. To simulate rivals' attributes, we draw the three residuals jointly from their empirical distribution, standardized by the binomial standard deviation of the predicted score, which preserves their correlation across dimensions and the lower dispersion of scores near the bounds of the unit interval.

E.3 Bid Inversion

For each auction, we draw 1,000 realizations of rivals' entry decisions, bids, and non-price attributes, which we use for all bidders and bids in that auction. To limit the influence of outliers, mostly due to errors in units, we drop observed bids below one third or above three times the median bid for the product, and restrict simulated bids to the same range. We evaluate the probability of winning on a grid of nine bids within 10 percent of the product's median bid around the observed bid, and estimate its derivative at the observed bid by local linear regression with an Epanechnikov kernel. The inversion sample contains 714,216 bids in 144,606 auctions.

Table E.2 reports the results. The inversion is well defined for 86 percent of bids. The remaining bids have a simulated probability of winning close to zero (8 percent), a derivative that is not negative (3 percent), or a negative implied cost (4 percent). The first two groups are bids far above those of their rivals, for which the first-order condition cannot be evaluated precisely by simulation. As the probability of winning goes to zero, the optimal markup goes to zero, so to obtain the distribution of effective costs used in the entry stage we set the effective cost of bids with a simulated probability of winning below 10^{-3} equal to the observed bid. Without them, the distribution of effective costs would omit the high-cost bidders that rarely win. The median markup over effective costs is 23 percent of the bid; markups are higher for large firms than for small firms (Table E.3).

Table E.2: Bid inversion: results

	Linear bid model	Gradient-boosted bid model
Panel A. Share of bids		
Inversion well defined	0.858	0.850
Probability of winning close to zero	0.077	0.078
Negative implied cost	0.037	0.045
Derivative not negative	0.028	0.027
Panel B. Markup, $(b - \hat{c})/b$, bids with a well-defined inversion		
Mean	0.282	0.278
10th percentile	0.100	0.093
Median	0.230	0.223
90th percentile	0.547	0.552
Bids	714,216	714,216
Auctions	144,606	144,606

Notes: Inversion of equation (7) with winning probabilities simulated from 1,000 draws of rivals' entry, bids, and non-price attributes per auction. The two columns differ in the model used to predict rivals' bids (Appendix E.2). The probability of winning is considered close to zero when it is below 10^{-4}.

Table E.3: Distribution of markups by firm size

	Small	Large
p10	0.092	0.110
p25	0.133	0.164
p50	0.200	0.254
p75	0.312	0.393
p90	0.480	0.571
Mean	0.260	0.315
SD	0.216	0.240
Observations	384,624	163,473

Notes: Markup over effective cost as a share of the bid, $(b - \hat{c})/b$, for bids with a well-defined inversion. Small firms have annual sales below 17 million USD.

E.4 Cost of Liquidity

Implementation. We estimate equation (12) on the bids with a well-defined inversion. The delay bins are 60–120 days, 120–180 days, and more than 180 days, relative to payment within 60 days, and $s_{it}(\tau)$ is the share of buyer i's invoices paid in each bin in year t. The linear part includes fixed effects for buyers, firms, products, years, months, and procedure types. We estimate the model by concentrated nonlinear least squares: given the nonlinear parameters $(\alpha_\tau, \theta_\tau)$, we compute the wedge and estimate the fixed effects by least squares, and we update $(\alpha_\tau, \theta_\tau)$ by Gauss–Newton steps until their largest change falls below 10^{-6}. Standard errors are clustered by buyer and year. We estimate the model separately for small and large firms.

Term structure. Table E.4 reports three specifications. Panel A leaves the cost of liquidity in each bin unrestricted. Point estimates are small and positive for delays of 60–120 days and larger for delays of 120–180 days, especially for small firms, for which the estimate of 4.4 log points is significant at the 10 percent level. The estimate for delays over 180 days is negative but imprecise, since few invoices are paid that late. Panel B imposes a constant monthly rate on the two intermediate bins, $\alpha_\tau = \log(1+\rho)\,(\tau - 1)$ with τ the bin's midpoint in months, and leaves the last bin unrestricted. This is the specification in Table 1. Panel C adds a quadratic term, $\alpha_\tau = \rho_1(\tau - 1) + \rho_2(\tau - 1)^2$. The curvature is positive for small firms and negative for large firms, consistent with long delays being disproportionately costly for small firms, but neither estimate is statistically different from zero.

Robustness. The estimates are similar when we split firms by their registered status as micro, small, or medium enterprises instead of by sales: the constant monthly rate is 0.78 percent for these enterprises and 0.87 percent for the rest. When we let the cost of liquidity in each bin vary with the

size of the contract relative to the firm's annual sales, $\mathbf{z}_{jt}$ in equation (11), the recovered wedge is flat in the size of the contract for both small and large firms (Figure E.2).

Table E.4: Cost of liquidity: alternative specifications

	All firms	Small firms	Large firms
Panel A. Unrestricted by bin, α_τ			
60–120 days	0.0133	0.0135	0.0184
	(0.0156)	(0.0157)	(0.0221)
120–180 days	0.0386	0.0444	0.0100
	(0.0237)	(0.0248)	(0.0276)
Panel B. Constant monthly rate			
$\log(1+\rho)$	0.0087	0.0098	0.0044
	(0.0048)	(0.0049)	(0.0060)
Panel C. Quadratic in the delay			
ρ_1	0.0036	0.0024	0.0159
	(0.0167)	(0.0169)	(0.0228)
ρ_2	0.0015	0.0022	−0.0033
	(0.0049)	(0.0050)	(0.0064)
Observations	587,293	416,089	171,168

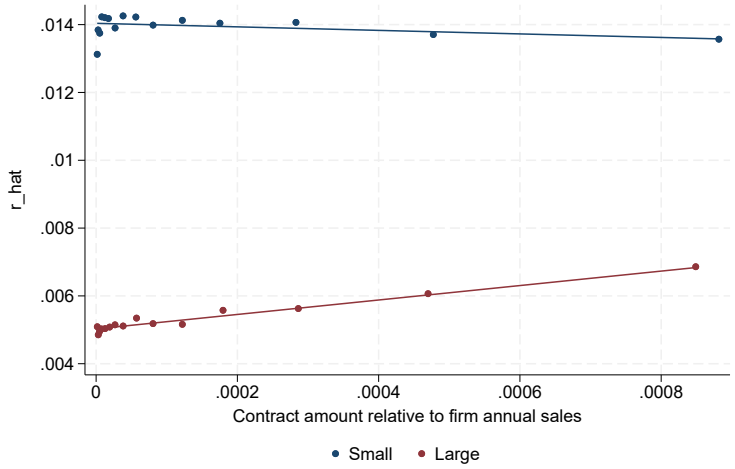
Notes: Nonlinear least squares estimates of equation (12), with log effective costs as the outcome. Delay bins are relative to payment within 60 days. In Panels B and C, the coefficient on delays over 180 days is left unrestricted (not reported). All specifications include buyer, firm, product, year, month, and procedure-type fixed effects. Small firms have annual sales below 17 million USD. Standard errors clustered by buyer and year in parentheses.

E.5 Expected Profits and Entry Costs

Distribution of effective costs. To compute expected profits for potential bidders that do not enter, we need the distribution of effective costs conditional on firm and auction characteristics. We regress the log effective cost, relative to the product's median bid, on buyer-by-year and product fixed effects, the firm's average log effective cost, log quantity, the firm's lagged sales and backlog, the procedure type, and whether the firm is located in the buyer's region. The residual standard deviation is 0.52. As for bids, we let it vary by product, with empirical Bayes shrinkage, and draw residuals from their empirical distribution.

Expected profits. For each potential bidder, we draw 20 effective costs from this distribution. For each draw, we compute the optimal bid against the same 1,000 draws of rivals used in the inversion, by grid search over bids between the cost and three times the product's median bid. We use a coarse grid of 30 points and then a fine grid of 30 points between the neighbors of the coarse maximum. When the probability of winning at the optimal bid is very low, the simulated profit function is

Figure E.2: Financing wedge and contract size



Notes: Binned scatter plot of the recovered financing wedge, $\hat{r}_{j,it}$, against the expected value of the contract relative to the firm's annual sales, for small and large firms. Specification of Panel B of Table E.4, with the cost of liquidity in each bin interacted with the contract-to-sales ratio. Auctions held by late payers in 2019.

nearly flat and the grid search can select spuriously high bids. We therefore move the bid toward the effective cost when the probability of winning is below 10^{-2}, fully so when it is below 10^{-3}, consistent with the treatment of these bids in the inversion. Expected profits are the average of the resulting profits across the 20 draws. We compute them for 2.8 million pairs of potential bidders and auctions in 145,334 auctions. The median expected profit is 3.2 percent of the product's median bid, with a 10th–90th percentile range of 0.4 to 11.9 percent.

Entry costs. We estimate equation (13) by two-stage least squares, with $\Phi^{-1}(\hat{\phi}_{j,ikt})$ as the dependent variable, where we bound $\hat{\phi}_{j,ikt}$ to $[10^{-4}, 1-10^{-4}]$. We normalize expected profits by the product's median bid. The coefficient on log expected profits net of the financing wedge identifies $1/\sigma$, and each control's coefficient divided by this coefficient identifies the corresponding element of $-\gamma$. The covariates $\mathbf{w}_{j,ikt}$ are log quantity, firm size, whether the firm is located in the buyer's region, whether the buyer is located in Santiago, and their interactions. The buyer fixed effects absorb the main effect of a Santiago location. We exclude the firm's backlog of contracts, which depends on its past entry decisions, and buyer-by-year fixed effects, which would absorb the variation in the financing wedge.

Table E.5 reports the estimates. Column (2) is the specification in Table 1. Column (1) omits the financing wedge, so it recovers the distribution of effective entry costs, $\kappa_{j,ikt}(1+r_{j,it})$. Since the wedge is small relative to the dispersion of entry costs, the two specifications are similar, and netting out the wedge lowers the estimated dispersion of log entry costs from 0.81 to 0.78. Instrumenting matters for the estimates: without instruments, the coefficient on log expected profits is 0.15, which implies a dispersion of log entry costs of 6.7, an implausibly large value. This is consistent with

measurement error in simulated expected profits and with their correlation with unobserved shocks to entry costs through rivals' entry, as discussed in Section 5.3.

The specification in Section 5.3 imposes that the wedge enters the entry decision with the same coefficient as expected profits. To test this restriction, we add $\log(1 + \hat{r}_{j,it})$ as a separate regressor with a free coefficient, and test whether this coefficient equals minus the coefficient on log expected profits. We do not reject the restriction ($p = 0.53$). The test has low power, however, because the buyer, product, and year fixed effects absorb most of the variation in the wedge.

Table E.5: Entry costs: instrumental-variables estimates

	(1) Effective entry costs	(2) Net of financing wedge
Log expected profits	1.230	1.286
	(0.059)	(0.062)
Log quantity	0.133	0.140
	(0.016)	(0.017)
Log quantity × large firm	0.033	0.034
	(0.007)	(0.007)
Large firm	−0.722	−0.770
	(0.055)	(0.056)
Same region	0.656	0.687
	(0.076)	(0.079)
Same region × Santiago	−1.625	−1.709
	(0.118)	(0.122)
Same region × large firm	−0.516	−0.512
	(0.238)	(0.250)
Same region × Santiago × large firm	0.684	0.665
	(0.261)	(0.275)
Santiago × large firm	0.299	0.330
	(0.112)	(0.116)
Dispersion of log entry costs, σ	0.813	0.777
	(0.039)	(0.037)
First-stage F-statistic	1,286	1,273
Observations	2,777,934	2,692,777
Buyers	187	187

Notes: Two-stage least squares estimates of equation (13). The dependent variable is $\Phi^{-1}(\hat{\phi}_{j,ikt})$. Expected profits are normalized by the product's median bid; in column (2), they are divided by $1 + \hat{r}_{j,it}$. Log expected profits are instrumented with the log number of potential bidders in the auction; the first-stage F-statistic is the Kleibergen–Paap Wald statistic. Coefficients are on the entry index; the implied effect of a covariate on the log entry cost is minus its coefficient times σ. All specifications include buyer, product, and year fixed effects. Large firms have annual sales of at least 17 million USD. Standard errors clustered by buyer in parentheses.