

Finance and Competition in B2B Markets: The Role of Factoring

Bernardo de Moura* Eliana Sena

Job Market Paper

University of Pennsylvania

October 28, 2026

[\[Latest version\]](#)

Abstract

In business-to-business markets, buyers often pay months after delivery, forcing sellers to finance their clients at potentially high borrowing rates. Factoring – the sale of unpaid invoices to a financial intermediary – gives suppliers cash today instead of waiting. We study its welfare and distributional effects across market participants. We develop a model of B2B markets in which sellers differ in material costs and loan rates. Sellers with high loan rates incur high costs from payment delays; factoring reduces these costs. Buyers differ in their preferences over suppliers and choose whichever supplier gives them the highest value net of price. We estimate the model using data from a factoring company. Comparing equilibria with and without factoring, we find that total welfare remains nearly unchanged. On the one hand, the reduction in financial costs leads to lower prices and welfare gains from output expansion. On the other hand, factoring reallocates production towards less efficient suppliers, generating losses from misallocation. These losses arise because reallocation raises production costs by more than it raises buyer value. Finally, in terms of distributional effects, lower interest payments reduce financial companies' revenues and benefit suppliers, who pass some of these gains to buyers through lower prices.

*I thank my advisors Juan Camilo Castillo, Ulrich Doraszelski, Aviv Nevo, and Juan Pablo Atal for their guidance and support.

1 Introduction

A distinctive feature of business-to-business (B2B) markets is that buyers usually purchase on *trade credit*, meaning that they pay invoices 30 to 120 days after delivery. During this period, sellers are making a loan to their clients. When the buyer can borrow at a lower rate than the supplier, this loan is inefficient because the buyer could finance the transaction more cheaply by paying on delivery. This inefficiency can prevent contracts that would generate positive surplus, particularly between small suppliers and large buyers.¹

Suppliers address this inefficiency by selling their unpaid invoices to a financial intermediary. This is called factoring. The intermediary pays the supplier today at face value minus a discount and collects payment from the buyer at the due date. Because the buyer is liable for payment, the interest rate follows the buyer’s borrowing rate rather than the supplier’s, allowing the supplier to finance the transaction at the lower rate and resolving the inefficiency. Despite this, factoring does not necessarily increase total welfare. On the one hand, factoring lowers suppliers’ effective costs and reduces prices. This increases demand and expands output, generating gains in total welfare. On the other hand, factoring reallocates production, which can have positive or negative effects on welfare. Buyers choose suppliers based on value net of price, while total welfare depends on value net of production costs. A less efficient supplier can therefore win business by charging a lower markup. Trade credit can reinforce this distortion if the resulting financing costs fall more heavily on higher surplus suppliers, or offset it if they fall on the lower surplus counterparts. By reducing the financial costs from trade credit, factoring can improve or worsen allocation.

In this paper we ask: What are the welfare effects of factoring? Our goal is to measure changes in total welfare as well as its distribution across buyers, suppliers, and the financial sector. We develop a model of B2B transactions in which each buyer has different preferences across suppliers. The buyer requests price quotes from all its suppliers and chooses the offer with the highest value net of price. Suppliers differ in their costs and set their quotes based on those costs and the competition they face. Using B2B transaction data, we estimate buyer preferences and supplier costs. We use these estimated parameters and observed interest rates to solve the model under two financing regimes. In one, suppliers can use factoring or bank loans; in the other, they can use only bank loans. Comparing the resulting equilibria lets us measure the effect of factoring on total welfare and its distribution across buyers, suppliers, and the financial sector.

For our analysis, we partnered with a Chilean factoring company (henceforth “Factor X”)

¹For example, the OECD reports that small and medium-sized enterprises (SMEs) in Chile faced loan interest rates of 11.2% in 2022, compared with 7.2% for large firms. See [OECD \(2024\), *Financing SMEs and Entrepreneurs*, Table 8.1](#).

to assemble a dataset that combines B2B transactions with firms’ financial records. When a supplier applies to Factor X, we gain access to all its invoices and financial records from the preceding two years, regardless of whether X approves the application. We continue observing these records until two years after its last transaction with X, or two years after application if it never transacts. We use these records to recover each supplier’s bank borrowing rate over time and the factoring rate for each contract.

We first estimate the effects of factoring on supplier activity without relying on structural models. We follow a judges IV design that exploits quasi-random assignment of applications to risk officers who differ in their willingness to approve invoices. We estimate that greater access to factoring increases suppliers’ revenues by about 3% by month five and raises their market shares by 0.35 percentage points. These results are in line with existing evidence that factoring helps suppliers grow ([Amberg et al., 2024](#); [Orestes et al., 2025](#)). However, these results alone do not answer our research question. Measuring welfare and distributional effects requires buyer preferences and production costs, which we recover using the model.

In our model, each buyer assigns a different value to each supplier. Before making a purchase, it requests quotes from a fixed roster and chooses the offer with the highest value net of price. Each time a supplier receives a request, it responds with a quote that maximizes its expected profit, given its effective marginal cost and the competition it faces. Effective marginal cost incorporates both the material cost of production and the cost of financing the payment delay. Each supplier privately observes its cost draw, while all participants know its effective-cost distribution. Suppliers finance the transaction through either bank loans or factoring and choose the lower rate when both are available. Loan rates vary across suppliers, but factoring rates depend largely on the buyer’s credit. Higher rates shift the cost distribution to the right, while lower rates shift it left. When deciding the optimal quote, the supplier faces a tradeoff: a higher quote increases profit if it wins but reduces its probability of winning. How this probability varies across quotes depends on the number of competitors, their effective-cost distributions, and the buyer’s preferences across suppliers. The optimal quote includes a markup over effective marginal cost, with a larger markup when a price increase is less likely to cost the supplier the sale.

We estimate the model in the road freight sector, where we observe buyers repeatedly purchasing from a stable roster of suppliers. Across hundreds of transactions, we see each buyer alternating among suppliers offering substitutable services. These repeated purchases let us measure each supplier’s share of a buyer’s orders and the distribution of winning prices for each relationship. Because we observe only winning quotes, these price distributions reflect selection into winning. To account for this selection, we combine each supplier’s winning-price distribution with those of its competitors and their respective shares of the buyer’s orders.

We show that these objects nonparametrically identify buyer preferences and supplier cost distributions over the range in which suppliers participate.² For computational tractability, we assume Weibull costs and jointly estimate preference and cost parameters from supplier shares and the first two moments of winning prices using generalized method of moments (GMM).

Our main finding is that the total effect of factoring on welfare is small and positive. Output expansion from factoring generates gains of about 7.5 cents per USD 100 of total volume factored; however, losses from misallocation of about 3.7 cents partially offset these gains, leaving a net gain of about 3.8 cents. The reallocation from factoring has a negative impact on welfare because it raises production costs by more than it raises buyer value. The markup distortion arises when suppliers that generate more surplus per transaction also charge higher markups, which shifts business toward lower-surplus competitors. Trade credit can counteract this distortion when these lower-surplus suppliers face higher financing costs. Their higher financing costs force them to increase their prices, which reduces their market shares and can bring market allocation of production closer to their efficient levels. Therefore, the trade credit distortion can improve the allocation of production. In lowering the trade credit distortion, factoring can reduce welfare through reallocation when it benefits less efficient suppliers.

Factoring has a significant impact on welfare distribution. In dollar terms, the largest effect is to lower interest payments: this reduces the financial sector’s revenues by about USD 1.98 per USD 100 of total volume factored. Suppliers retain most of these savings, gaining about USD 1.22 on the same basis. However, the effects across suppliers differ sharply. Factoring has disparate effects on rate reductions. Most suppliers receive little or no reduction in their financing rates but face stronger competition from suppliers whose rates fall substantially. So factoring actually has a negative effect on surplus for more than half of suppliers. The suppliers with the largest financing-rate reductions, representing 21.2% of the sample, account for 74.4% of suppliers’ aggregate net gain. Finally, buyers gain about 79 cents per USD 100 factored, including about 76 cents from lower prices and another 3 cents from reallocation toward suppliers they value more highly, net of the associated increase in payments.

These findings have broader implications for policies that expand firms’ access to finance, such as small business loan programs. Such policies can help recipients grow without increasing total welfare when their expansion displaces production from firms that generate more surplus.

²Our argument recovers supplier costs using the inversion logic of [Guerre, Perrigne, and Vuong \(2000\)](#), conditional on buyer preferences. In estimation, we recover these preferences by matching supplier winning shares conditional on cost parameters.

Financing distortions can reinforce or offset markup distortions, so easing financing constraints need not improve allocation. Evaluating these policies therefore requires accounting for which firms gain business and which competitors they displace, alongside the gains from additional output.

Related literature and contributions. This paper contributes to the empirical literature on factoring. Although empirical work remains limited, existing studies highlight two benefits of factoring. First, factoring can expand suppliers’ access to finance by relying on their buyers’ creditworthiness (Klapper, 2006). Second, suppliers who gain access to invoice financing or face lower factoring rates tend to increase their sales (Amberg et al., 2024; Figal Garone et al., 2026; Orestes et al., 2025).³ Orestes et al. (2025) also use a quantitative model to estimate the aggregate output gains from lower factoring rates. Our billing point estimate is positive, although its confidence interval includes zero. Our contribution is to measure the welfare effects of factoring in markets where suppliers have market power. Our model captures both the gains from output expansion and the potential losses from reallocation when financing costs partly offset markup distortions. We also measure changes in surplus for buyers, suppliers, and the financial sector.

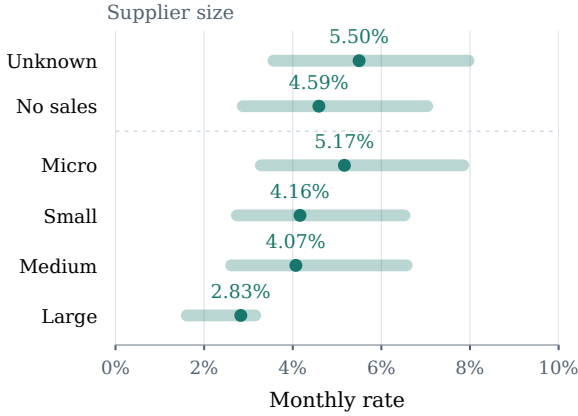
This paper also contributes to the literature on access to finance and firm outcomes. Earlier work, including Banerjee and Duflo (2014) and Brown and Earle (2017), shows that expanded credit access can increase firms’ production, revenues, profits, and employment. A second generation of papers, including Rotemberg (2019) and Cai and Szeidl (2024), shows that the aggregate effects are more complicated. While recipients gain, losses at competing firms offset much of these direct benefits. These papers nevertheless identify gains from reallocation and improved outcomes for consumers. Rotemberg finds that reallocation toward firms with higher marginal products raises aggregate productivity. Cai and Szeidl find that lower prices and better quality generate substantial consumer gains. Our contribution is to study these equilibrium effects in the context of factoring, a different form of finance. In contrast with Rotemberg, reallocation reduces welfare in our setting because production shifts toward less efficient firms. Our finding of gains to buyers is consistent with Cai and Szeidl. Beyond these differences in results and financial technology, we also take a different methodological approach.

On the methods, we build on empirical work that uses auction models to study pricing and competition in B2B and credit markets. Previous work focuses on homogeneous goods and combines auction models with search or limited consideration (Salz, 2022; Allen et al.,

³Amberg et al. (2024) and Figal Garone et al. (2026) use difference-in-differences designs to study reverse-factoring adoption. Orestes et al. (2025) exploit fund flows to factoring intermediaries to instrument suppliers’ factoring rates.

Figure 1: Own-financing and factoring interest rates

A. Own-financing rates



B. Factoring interest rates



Notes: Dots show medians; bars show the 25th–75th percentiles. The horizontal scales differ. Panel A uses our imputed own-financing proxy for 46,819 equally weighted supplier-months and 5,771 suppliers with accepted, operated X offers; the large group contains eleven suppliers. Panel B excludes commissions and compares four ordered buyer-risk categories using 918 offers from 25 suppliers and 475 buyers. We give each category the same joint distribution of suppliers, issue months, advance bands (up to USD 1,000; USD 1,000–5,000; above USD 5,000), and term bands (up to 30; 31–60; above 60 days). Buyer assessments come from a snapshot. The own-financing proxy does not measure observed bank rates, and the two panels do not measure within-invoice savings. Appendix Table E.6 reports coverage and construction details.

2019; Cuesta and Sepulveda, 2021). We instead combine empirical first-price auction models (Guerre et al., 2000) with differentiated-product demand (Berry et al., 1995). This allows us to study markets with differentiated goods: buyers value suppliers’ products differently and do not just choose the lowest quote.⁴

2 Institutional Setting and Data

Factoring finances a large and growing volume of business-to-business transactions in Chile. Suppliers sell their unpaid invoices to factoring companies; these then collect payment from the buyers when the invoice falls due. The nominal annual value of electronic invoice sales rose quickly from USD 0.4 billion in 2008 to USD 13 billion in 2015 and USD 49 billion in 2025, equivalent to about 15% of GDP (Appendix Figure E.1).

2.1 Data and Sample

Our main data source is a Chilean factoring company, which we call Factor X. Suppliers who wish to sell invoices to X must first apply for financing and link their transaction and

⁴Beckert et al. (2026) also study differentiated products and estimate preferences and costs from B2B transaction data. However, they model bargaining with complete information about costs and valuations, so the supplier that generates the highest surplus wins every transaction and misallocation does not arise.

financial records.⁵ This step gives X access to their broader business activity before it decides whether to approve financing. Our sample therefore consists of suppliers that apply to X and the buyers they trade with. We observe applicants’ full invoice histories and financial records before and after application, whether or not X approves their requests. These histories include invoices that applicants never submit for financing.

For this selected sample we have access to the universe of transaction and financial data over a window starting two years before application through two years after the supplier’s last transaction with X, or two years after application if it never transacts with X. The electronic invoice histories and historical sales-size classifications come from Chile’s tax authority (SII). For each invoice, we observe the buyer and supplier, face value, issue and recorded due dates, and the assignee if the supplier transfers the invoice. We use firm and invoice identifiers to link the tax data to X’s application and financing records and to firm characteristics, including sectors, locations, and X’s credit assessments. X also provides its application decisions and financing offers, including interest, commissions, and advances, and payment dates for invoices it finances.

2.2 Summary Statistics

In our sample, we observed suppliers of many different sizes and sectors. However, throughout all groups, we see that large buyers account for the largest share of sales. Across suppliers’ full invoice histories, large buyers account for 46% of micro suppliers’ sales and about 64% of medium and large suppliers’ sales (Appendix Figure E.2). These relationships matter for financing because X sets its factoring rates partly according to the buyer’s credit risk. Factoring therefore allows a supplier to finance an invoice at the factoring rate associated with its buyer. When the all-in factoring rate falls below the supplier’s own-financing rate, the supplier can lower the cost of extending trade credit by selling the invoice. For a given factoring rate, this financing advantage grows as supplier size falls and own-financing rates rise, making factoring potentially more valuable to small and micro suppliers.

Loan rates tend to increase as supplier size falls, while Factor X sets its factoring terms partly according to the buyer’s credit risk. Figure 1A shows median monthly benchmark rates of 5.2% for micro suppliers and 2.8% for large suppliers, although the large group contains only eleven firms. Figure 1B compares X’s factoring offers across buyer-risk categories with the same mix of suppliers and financing terms. Median monthly interest rates rise from 1.8% in the lowest-risk category to 2.3% in the highest. X charges commissions as well as interest, so a supplier’s potential gains from factoring depend on the all-in cost of financing

⁵Applicants authorize X to retrieve their transaction and financial records electronically, including the electronic invoice histories that Chile’s tax authority (SII) maintains.

Table 1: Applicant characteristics and factoring use by supplier size

	All	Micro	Small	Medium	Large
Median annual sales (USD)	102,100	51,700	282,400	1,634,700	6,481,700
Median largest-customer share (%)	47.0	49.3	42.7	37.8	34.1
Sales to larger buyers (%)	53.7	90.0	79.4	65.0	0.0
Suppliers with any assignment (%)	44.5	34.3	56.6	74.8	77.5
Invoice value assigned (%)	22.9	8.3	20.2	30.6	30.6
Suppliers	11,723	5,515	3,749	555	138

Notes: We use the twelve complete months before application for applicants whose histories reach the start of that window. All includes 1,481 suppliers with unknown size and 285 with no sales. We classify both counterparties using historical SII sales at the supplier’s application. The larger-buyer row uses sales with comparable size categories, covering 78.2% of all invoice value and 48.0% for micro suppliers; no category exceeds Large. Assignments refer to any factor and can occur after application. We weight medians and participation equally across suppliers and the two value shares by invoice value. Appendix Table E.3 reports valid counts, size coverage, and the two omitted size groups. Amounts in USD; we round to the nearest USD 100.

each invoice. To compare total financing costs, we include commissions and evaluate both alternatives over the same financing period.

3 Descriptive Evidence

In this section, we provide evidence on how access to factoring affects supplier activity and competition for buyers’ business in B2B markets. We cannot simply compare firms that use factoring with those that do not, because unobserved firm characteristics may affect both factoring use and supplier activity. To address this selection problem, we exploit a quasi-random variation in the firms that have access to Factoring. Using this variation, we find suggestive evidence that greater initial approval increases suppliers’ revenues and market shares.

3.1 Empirical Approach

Our goal is to estimate the causal effect of access to factoring on supplier outcomes. Consider the following regression:

$$Y_j = \alpha + \beta \text{Access}_j + X_j' \gamma + \varepsilon_j, \quad (1)$$

where Y_j denotes an outcome for supplier j , such as revenues or its share of buyers’ observed purchases, Access_j measures its access to factoring, and X_j contains observed controls. The coefficient β represents the causal effect we seek to estimate. To get a consistent estimate of β , we need to deal with two sources of selection. First, suppliers choose whether to seek access to factoring, often in response to high borrowing costs or credit constraints. These financing

conditions may also affect supplier revenues and other outcomes independently of access to factoring, creating a selection problem. Second, factoring requires a financial intermediary to purchase the invoice, and its risk team must approve the transaction. Suppliers who receive approval may differ from rejected applicants in unobserved characteristics that also affect their outcomes, creating a second source of selection. Both decisions can therefore correlate access to factoring with ε_j , so we cannot hope to get a causal estimate of β using ordinary least squares.

To address the selection problem, we use a judge-leniency instrument, exploiting how our data partner, Factor X, chooses its clients. Any supplier seeking to sell invoices to X must first submit an application. A risk officer then reviews the application and decides whether to approve financing. Officers differ in their willingness to approve invoices, or *leniency*. We measure the leniency of supplier j 's initial officer using that officer's monthly approval share, excluding all decisions involving supplier j :

$$Z_j = \frac{\sum_{d \in \mathcal{D}_j} A_d}{|\mathcal{D}_j|},$$

where $\mathcal{D}_j$ contains the officer's approval and rejection decisions on other suppliers' invoices in the relevant month, and A_d equals one for approval and zero for rejection. This *leave-one-out* measure prevents the supplier's own approval from mechanically entering the instrument. We use Z_j as an instrument for the share of invoices that Factor X approves in the supplier's initial application. This instrument is relevant in the sense that it has statistically and economically significant impacts on access to factoring: the left panel of Figure 2 shows that a 10-percentage-point increase in officer leniency predicts approximately 2 percentage points more initial approval. The heteroskedasticity-robust first-stage F -statistic is 22.58.

Our identifying assumption is that risk officer assignment to suppliers is as good as random within application month. For example, if a supplier applies in January 2024 and five officers review applications that month, which officer it encounters may affect its probability of gaining access to factoring through leniency, but should not affect supplier outcomes through channels other than access to factoring. Factor X's routing rule supports this assumption. Every day, several officers review applications concurrently, each with a queue of pending cases. When a supplier applies, X automatically routes its application to the officer with the shortest queue; these queues change as applications arrive and officers complete their reviews, thus making assignment as good as random. To further support our argument that the instrument is clean, we run a placebo test of the effects of assignment on pre-application outcomes. We find no statistically significant differences across initial officers, controlling for application month (Appendix Table 4). While these tests do not rule out sorting on

unobserved characteristics, we can at least show that the routing rule works as advertised on observables.

In our empirical setting, we study access to factoring through Factor X’s initial approval decisions. We estimate the following equation by two-stage least squares (2SLS), using officer leniency Z_j as an instrument for initial approval A_j :

$$Y_{jh} - Y_{j,-1} = \alpha_h + \beta_h A_j + X'_j \gamma_h + \varepsilon_{jh}. \quad (2)$$

Here, Y_{jh} denotes supplier j ’s outcome in event month h , and we measure changes relative to month -1 . Thus, β_1 measures the effect of initial approval on the change in Y_j from month -1 to month 1.⁶ We study changes rather than levels to remove the effects on outcome levels of supplier characteristics that remain constant over time.⁷ We control for the month and year of the earliest invoice in each supplier’s initial application: we therefore compare suppliers whose initial invoices date from the same calendar month, accounting for seasonal and macroeconomic conditions common to those suppliers. Under our identifying assumptions, these estimates capture local average treatment effects (LATEs): the effect of additional approval for suppliers who would receive more approval from a lenient officer than from a stricter one. Appendix Section A.5 describes the estimation details.

3.2 Supplier Growth and Competition

We find that gaining access to factoring has a positive effect on several indicators of supplier firm growth. For brevity, we now focus on three outcomes: sales of invoices to Factor X, total monthly revenues, and suppliers’ share of their buyers’ observed purchases.⁸ Consistent with access to factoring actually increasing factoring usage, we find that it sharply increases the probability that a supplier sells an invoice to Factor X at month zero, with the estimated effect declining overall to about 42 percentage points by month five (Figure 2, right panel). We also estimate that approval increases total monthly revenues by about 4% at month two, declining to about 1.7% by month five (Figure 3, left panel).⁹ Finally, we estimate that approval increases suppliers’ share of their buyers’ observed purchases by 0.58 percentage points at month four, relative to a pre-period average share of 15.1% (Figure 3, right panel).

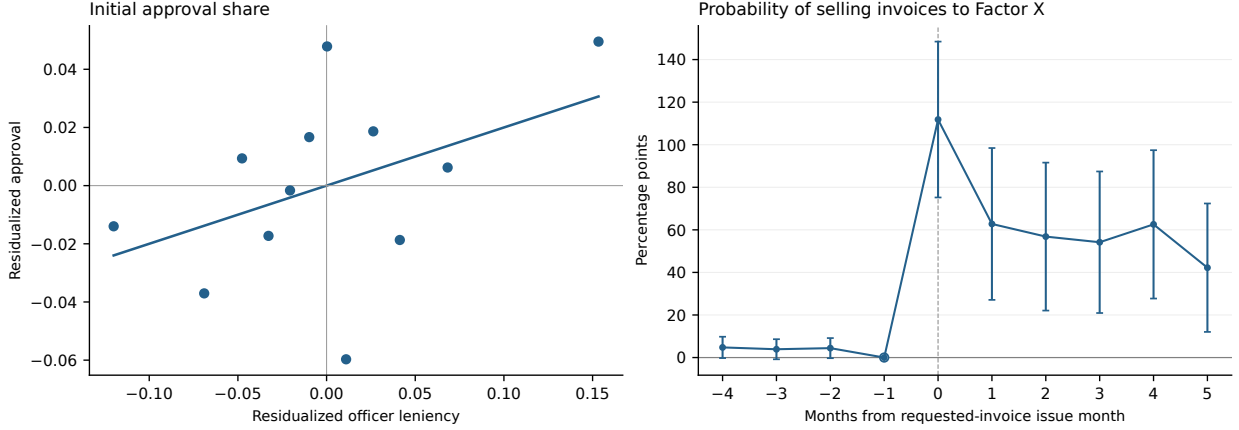
⁶The coefficients β_{-2} , β_{-3} , and β_{-4} serve as placebo tests: they test for effects of approval on supplier outcomes before the initial invoice month, when approval should have no effect.

⁷For example, better-managed firms may both use factoring more often and earn higher revenues; differencing removes any revenue advantage that remains constant over time.

⁸Appendix Section A.1 reports the complete 2SLS results, including factoring with any provider, invoice counts, average invoice value, buyer counts, sales to buyers absent in the reference month, billing to existing buyers, rivals’ billing, buyer size and composition, competitors’ purchase shares, and factoring rates.

⁹Appendix Section A.5 describes the outcome transformation.

Figure 2: Officer leniency, approval, and factoring use

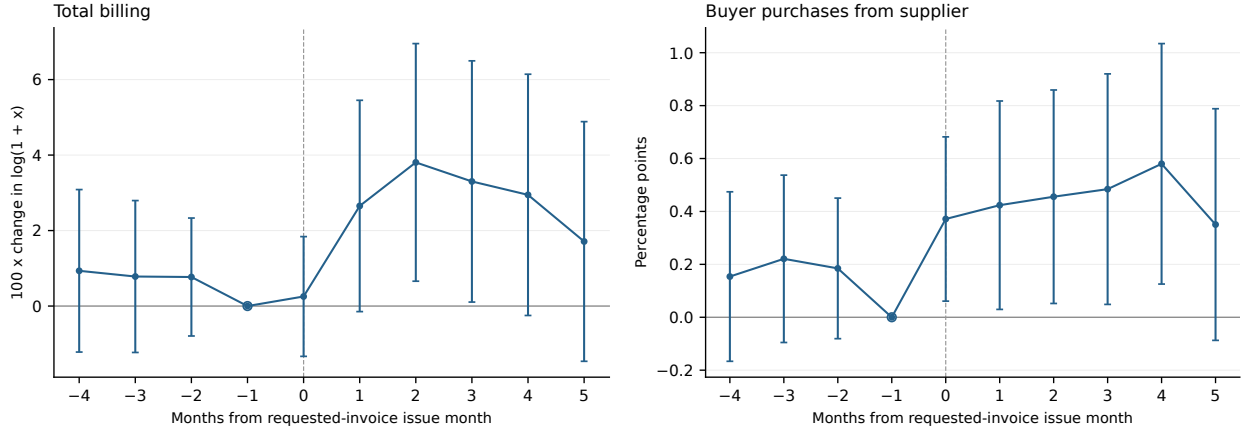


Notes: Left: twelve bins and the fitted approval-share first stage after removing billing-group by invoice-event-cohort means. Right: percentage-point IV effects on the probability of selling at least one invoice to Factor X in that month for a 0-to-1 change in any initial approval. Both stages use 25,468 suppliers. Outcome whiskers show 95 percent confidence intervals; month -1 is the zero reference.

These results suggest that access to factoring affects both supplier growth and competition for buyers' business. Higher revenues suggest that suppliers expand their sales, while larger purchase shares indicate that they gain ground relative to other suppliers serving the same buyers. Correspondingly, competitors' shares of these buyers' purchases decline (Appendix Figure 10). Suppliers may therefore grow both by generating additional business and by attracting purchases that buyers would otherwise make from competitors. As discussed in the introduction, Rotemberg (2019) and Cai and Szeidl (2024) show that gains from financial support can come partly at competitors' expense. Our estimates do not distinguish these channels: a supplier can gain purchase share even if its competitors' sales also increase.

These results leave open the question of whether factoring increases aggregate welfare. When factoring shifts business across suppliers, the welfare effect depends on whether the suppliers gaining sales create more value for buyers, net of production costs, than those losing sales. Supplier growth alone therefore does not establish whether factoring improves the allocation of resources. To assess these welfare effects, we need to distinguish output expansion from reallocation and account for the responses of other market participants. We therefore develop and estimate a model of supplier competition for buyers' business that allows us to quantify these channels and their welfare implications.

Figure 3: Initial approval, billing, and share of buyer purchases

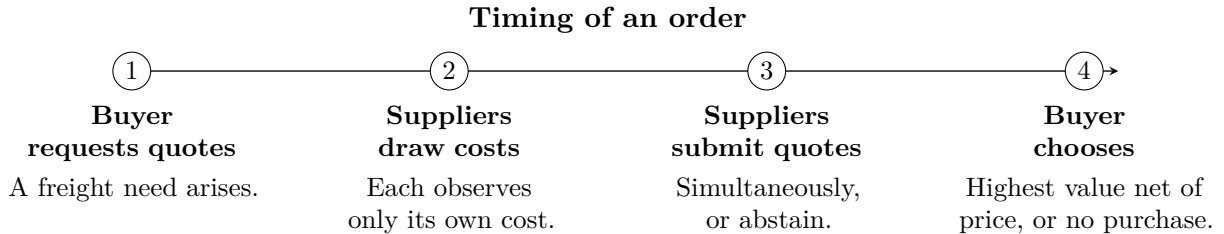


Notes: Both panels show IV effects for a 1.4-percentage-point increase in initial approval share. Left: 100 times the change in $\log(1 + \text{total billing})$, with billing in thousands of USD before taking logs. Right: the supplier's share of its buyers' observed purchases, in percentage points. We fix each supplier's buyer roster to every buyer with which it trades anywhere in the observed history. At month five, the billing sample contains 12,748 suppliers and the purchase-share sample contains 11,707; the common first stage uses 25,468 suppliers. Whiskers show 95 percent confidence intervals; month -1 is the zero reference.

4 Model

The descriptive evidence above covers suppliers across sectors. We now focus on road freight, modeling each order as a choice among suppliers that can meet the buyer's transportation need. The sector features frequent transactions between buyers and suppliers, an important statistical advantage for estimation.

We develop a model of B2B transactions to study how factoring affects prices, allocation, and welfare in freight markets. Buyers request quotes and choose the supplier that offers the highest value net of price. Suppliers respond with price quotes that maximize their expected profits. Their costs include the material costs of production and the financial costs of extending trade credit. Factoring lowers these financing costs, affecting both suppliers' own quotes and their competitors' pricing. Financing costs affect total output and, together with markups, they also determine which suppliers win.



4.1 Game setup

Each buyer i has a fixed roster of suppliers J_i . We model the buyer's demand for freight services as repeated orders indexed by a . For each order, the buyer requests quotes from its roster. Its utility from purchasing from supplier j is

$$u_{ija} = \delta_{ij} - B_{ija}, \quad (3)$$

where δ_{ij} is buyer i 's value for supplier j 's service and B_{ija} is supplier j 's price quote.¹⁰ We hold δ_{ij} fixed across orders and assume common knowledge of each buyer's roster and values. We normalize the utility of no purchase to $u_{i0a} = 0$.¹¹

Suppliers are risk neutral and maximize expected monetary profit. For buyer i 's order a , supplier j faces a random cost $c_{ija} \sim F_{ij}$ that combines production and financing costs. We assume independent cost draws across suppliers and orders. Before submitting a quote, each supplier knows its rivals' cost distributions and observes only its own cost realization. Let $W_{ij}(b)$ denote supplier j 's probability of winning with quote b , given its rivals' bidding strategies. The supplier solves the equivalent pricing problem

$$\max \left\{ 0, \sup_{0 \leq b \leq \delta_{ij}} (b - c_{ija}) W_{ij}(b) \right\}. \quad (4)$$

The zero option represents abstention.

Suppliers' cost distributions depend on the interest rates they face and the distribution of their material costs of production. Let $c_{ija}^{\text{prod}} \sim F_{ij}^{\text{prod}}$ denote supplier j 's production cost and $r_{ij} \in [0, 1)$ the financing payment as a fraction of sale value over the full payment term. We take r_{ij} as exogenous and hold it fixed across orders and quotes. We write $c_{ija} = c_{ija}^{\text{prod}} / (1 - r_{ij})$.¹² Holding production-cost distributions fixed, higher interest rates shift suppliers' cost distributions to the right, and lower rates shift them to the left. We assume common knowledge of these distributions, which incorporate the financing conditions relevant for bidding.

We model factoring as an additional financing option for suppliers. Let r_{ij}^{bank} and r_{ij}^{fac} denote the supplier's bank and factoring interest rates. A supplier with access to both chooses

¹⁰We measure both in dollars and normalize the coefficient on the bid to -1 .

¹¹The buyer chooses $j^*(a) \in \arg \max_{j \in J_i \cup \{0\}} u_{ija}$, where $j^*(a) = 0$ denotes no purchase. For bookkeeping, we assign $B_{ija} = +\infty$ to abstention. The buyer chooses uniformly among tied inside suppliers with the highest acceptable score and favors an inside supplier when its score ties the outside payoff of zero. A bid above δ_{ij} cannot win, so we treat it as abstention.

¹²Multiplying the supplier's objective by $1 - r_{ij}$ gives expected monetary profit. This positive factor does not depend on the quote, so it leaves the optimal quote unchanged.

$r_{ij} = \min\{r_{ij}^{\text{bank}}, r_{ij}^{\text{fac}}\}$.¹³ When $r_{ij}^{\text{fac}} < r_{ij}^{\text{bank}}$, access to factoring lowers its financing rate and shifts its cost distribution F_{ij} to the left. We compare outcomes with and without factoring while holding buyer tastes, supplier rosters, and material production-cost distributions fixed.

4.2 Equilibrium pricing

The probability of winning depends on a supplier's own quote, the buyer's valuations, and its rivals' cost distributions and bidding strategies. Let $\sigma_{ik}(c)$ denote supplier k 's bidding function, the quote it submits to buyer i when it participates at cost c . For strictly increasing bidding functions, let σ_{ik}^{-1} denote the inverse bidding function.¹⁴ At a quote $0 \leq b \leq \delta_{ij}$, supplier j wins when every rival k quotes more than $b + \delta_{ik} - \delta_{ij}$ or abstains. Independent cost draws therefore give

$$W_{ij}(b) = \prod_{k \in J_i \setminus \{j\}} \left[1 - F_{ik}(\sigma_{ik}^{-1}(b + \delta_{ik} - \delta_{ij})) \right]. \quad (5)$$

Each factor gives the probability that one rival submits a worse offer or abstains. This gives the winning probability that enters the supplier's pricing problem above.

A supplier's markup depends on how sensitive its probability of winning is to its quote. Raising the quote increases its margin if it wins but reduces its chance of winning. At an interior optimum where W_{ij} is differentiable, the first-order condition relates cost c to the optimal quote $b = \sigma_{ij}(c)$:

$$b = c + \frac{W_{ij}(b)}{-W'_{ij}(b)}.$$

The second term is the supplier's markup over cost. The markup is smaller when a higher quote causes a larger proportional decline in the probability of winning.¹⁵ This sensitivity reflects the competitive environment: rivals whom the buyer values more highly, or who have lower cost distributions, can make winning more sensitive to the supplier's quote and constrain its markup.

Factoring affects a supplier's own markup and quote as well as those of its rivals. By lowering financing costs, factoring puts downward pressure on suppliers' own quotes through cost pass-through and on their rivals' quotes through stronger competition. As Section 4.1 explains, a lower financing rate shifts a supplier's cost distribution to the left. Suppliers

¹³We assume suppliers face no additional fees or financing constraints when choosing between these offers.

¹⁴In Appendix B.3, we extend the inverse to quote thresholds outside the range of quotes that the supplier submits.

¹⁵Let $\varepsilon_{ij}(b) = -bW'_{ij}(b)/W_{ij}(b)$ denote the absolute price elasticity of the winning probability. The first-order condition implies $(b - c)/b = 1/\varepsilon_{ij}(b)$, so the markup as a share of the quote equals the inverse elasticity.

can retain part of these cost savings as higher markups and pass part through to buyers as lower prices. The cost shift also changes rivals' winning probabilities and their sensitivity to quotes, affecting rivals' markups even if their own financing rates and the buyer's tastes remain unchanged.

We define a Bayes–Nash equilibrium as a set of bidding strategies under which each supplier chooses a quote or abstains to maximize expected profit conditional on its cost, given its rivals' strategies and the buyer's choice rule. We assume independent private costs and continuous, strictly positive cost densities over the range where suppliers participate. Under these assumptions, we prove existence and uniqueness of the Bayes–Nash equilibrium for buyers with at least two suppliers.¹⁶ Appendix B.2 gives the full proof. Suppliers' equilibrium quotes increase continuously and strictly with their costs when they participate. Given a buyer's roster, its valuations and suppliers' cost distributions therefore uniquely determine equilibrium bidding functions, winning probabilities, and markups.

The equilibrium bidding function expresses each supplier's quote as its cost plus a markup. Let $P_{ij}(c) = W_{ij}(\sigma_{ij}(c))$ denote supplier j 's probability of winning when it submits its equilibrium quote at cost c . For participating costs $c < \delta_{ij}$, the bidding function satisfies

$$\sigma_{ij}(c) = c + \frac{1}{P_{ij}(c)} \int_c^{\delta_{ij}} P_{ij}(u) du. \quad (6)$$

The upper limit δ_{ij} is the participation cutoff, at which the supplier earns zero profit.¹⁷ In Appendix B.3, we use these bidding functions to derive supplier shares and the mean and variance of prices conditional on winning.

4.3 Allocation and welfare

Total surplus equals buyer value less material production costs across all completed transactions. We assume that financial firms incur no marginal resource cost. For each buyer i , the indicator $\mathbf{1}\{j^*(a) = j\}$ equals one when supplier j wins order a , and zero otherwise. We define total welfare as

$$S = \sum_i \sum_a \sum_{j \in J_i} \mathbf{1}\{j^*(a) = j\} (\delta_{ij} - c_{ija}^{\text{prod}}). \quad (7)$$

¹⁶Appendix B.1 states the full assumptions, including the support restrictions and the condition on cost probability near the participation cutoff.

¹⁷When $c = \delta_{ij}$, a quote above the buyer's valuation cannot win, while a quote below it yields a loss if the supplier wins. The supplier can therefore quote δ_{ij} or abstain, earning zero profit in either case.

An order that ends in no purchase contributes zero surplus because all its winner indicators equal zero. We obtain expected welfare, $\mathbb{E}[S]$, by averaging over material production-cost draws.

The efficient allocation maximizes surplus separately for each order. Let $j^{\text{eff}}(a)$ denote the efficient choice for buyer i 's order a . For each realization of material production costs,

$$j^{\text{eff}}(a) \in \arg \max_{j \in J_i \cup \{0\}} \left\{ \delta_{ij} - c_{ija}^{\text{prod}} \right\}, \quad (8)$$

where we set $\delta_{i0} = c_{i0a}^{\text{prod}} = 0$ for no purchase. Note that financing costs do not enter this efficiency criterion. Under our assumption that financial firms incur no marginal resource cost, financing payments transfer surplus between suppliers and financial firms. The efficient allocation leaves an order unfilled if every supplier generates negative surplus. A supplier with higher production costs can be the efficient choice if the buyer's greater valuation of its service outweighs the cost difference.

The market allocation can differ from the efficient allocation because suppliers' quotes include two wedges above material production costs: a financing wedge and a markup. Given equilibrium quotes, the buyer chooses

$$j^*(a) \in \arg \max_{j \in J_i \cup \{0\}} \left\{ \delta_{ij} - B_{ija} \right\}, \quad (9)$$

where we set $B_{i0a} = 0$ for no purchase. For a supplier that submits a quote, we can decompose its price as

$$B_{ija} = c_{ija}^{\text{prod}} + \underbrace{\frac{r_{ij}}{1 - r_{ij}} c_{ija}^{\text{prod}}}_{\text{financing wedge}} + \underbrace{(B_{ija} - c_{ija})}_{\text{markup}}. \quad (10)$$

Differences in financing wedges and markups can lead the buyer to select a supplier that generates less total surplus than another available supplier. Financing costs can also prevent trades that would generate positive surplus. If S^{eff} denotes welfare under the efficient allocation, the welfare loss is $S^{\text{eff}} - S \geq 0$.

Factoring can increase or decrease total welfare through its effects on allocation and total output. In our counterfactual analysis, we compare expected welfare across equilibria with and without factoring, holding buyer tastes, supplier rosters, and material production-cost distributions fixed. We allow all suppliers to adjust their pricing rules, including those whose own financing rates remain unchanged.¹⁸ Lower financing costs need not move production toward suppliers that generate more surplus, as financing differences may offset differences

¹⁸These suppliers may adjust their quotes in the new equilibrium because factoring changes their rivals' cost distributions.

in markups. Reallocation can therefore raise or lower welfare. Factoring can also increase expected total output: lower financing costs can bring a supplier's cost below the buyer's valuation on an order for which all suppliers would abstain under bank credit alone. These additional transactions generate welfare gains from output expansion.

Prices and financing payments determine how buyers, suppliers, and financial firms share total surplus. We define buyer surplus CS as value less price, supplier surplus PS as revenue net of financing payments and material production costs, and financial-sector surplus FS as financing receipts:

$$\begin{aligned} CS &= \sum_i \sum_a \sum_{j \in J_i} \mathbf{1}\{j^*(a) = j\} (\delta_{ij} - B_{ija}), \\ PS &= \sum_i \sum_a \sum_{j \in J_i} \mathbf{1}\{j^*(a) = j\} \left[(1 - r_{ij}) B_{ija} - c_{ija}^{\text{prod}} \right], \\ FS &= \sum_i \sum_a \sum_{j \in J_i} \mathbf{1}\{j^*(a) = j\} r_{ij} B_{ija}. \end{aligned} \tag{11}$$

We assign zero to nonwinning terms and to orders that end in no purchase. These components satisfy $S = CS + PS + FS$. We obtain expected surplus for each group by averaging over material production-cost draws. Holding production costs and the allocation of orders fixed, prices and financing payments redistribute surplus without changing total welfare.

4.4 Limitations

We hold buyer–supplier valuations fixed across repeated orders and omit order-specific taste shocks. Variation in suppliers' costs and the resulting quotes therefore drives changes in which supplier wins. This assumption rules out changes in buyers' relative valuations across orders—for example, a buyer may value a supplier's delivery speed more when a shipment becomes urgent. Such changes could alter the elasticity of winning probabilities with respect to quotes and therefore suppliers' equilibrium markups. They could also change which allocation maximizes total surplus. If these changes matter in the data, our model may attribute some variation in supplier choices to costs, with implications for estimated markups and welfare effects.

We hold supplier rosters and material production-cost distributions fixed across financing regimes. We do not model market entry or exit, the formation of new buyer–supplier relationships, or investment that changes suppliers' production costs or capacity. Our counterfactuals therefore describe factoring's effects within existing supplier relationships and production technologies.

We take bank and factoring interest rates as given and assume that suppliers face no

additional fees or borrowing limits. We therefore omit lenders' pricing responses to changes in competition between financing technologies. In our model, factoring can enable additional orders only through reductions in interest rates.

We assume that financial firms incur no marginal resource cost, so financing payments redistribute surplus without changing total welfare for a given allocation. If banks and factoring firms incur costs for screening, monitoring, or collection, factoring can also affect welfare by changing the resources that financial intermediation requires. Our welfare measure omits these effects, including any intermediation costs associated with additional transactions.

5 Estimation

We estimate buyers' preferences over suppliers and suppliers' marginal cost distributions to quantify how factoring affects markups, the allocation of production, and welfare. Our data record the winning supplier and transaction price for each purchase, but do not reveal losing bids or suppliers' costs. We estimate these primitives jointly using generalized method of moments (GMM), matching suppliers' winning shares and fitting the first two moments of prices conditional on each supplier winning.

5.1 Empirical specification

In this subsection we describe the parametric assumptions on marginal costs and preferences, and how the parameters determine the moments we use in estimation: winning shares and the first two moments of prices conditional on each supplier winning. Although we present these moments separately, we estimate all parameters jointly using both sets of moments.

We model suppliers' marginal costs as draws from Weibull distributions. With infinite data, we could identify relationship-specific cost scales and shapes from winning-price distributions and supplier shares (Section 5.2). To improve precision with limited data, we pool across relationships, estimating five group-specific scales $\lambda_g^C > 0$ and five group-specific shapes $\kappa_g > 0$. We assign relationship (i, j) the scale $\lambda_{g(i,j)}^C$ and shape $\kappa_{g(i,j)}$, where $g(i, j) \in \{1, \dots, 5\}$ denotes its cost group.¹⁹ The group scales allow cost levels to vary. These cost parameters, together with the free preference parameters δ_{ij} , form the full parameter vector we estimate, $\theta = (\{\delta_{ij}\}_{i,j}, \{\lambda_g^C\}_{g=1}^5, \{\kappa_g\}_{g=1}^5)$.

We impose no functional form assumption on suppliers' bidding functions σ_{ij} . However, in order to map the model parameters into moments, we must first estimate these functions.

¹⁹We form the groups from preliminary estimates of each relationship's marginal production-cost scale and hold membership fixed during estimation. A supplier can belong to different groups across buyers because we classify relationships.

To do this we assume each supplier chooses a best response function to maximize expected profit conditional on its cost and its rivals' strategies. In the model appendix, we prove existence and uniqueness of equilibrium under the model's assumptions (Theorem 1). Thus, θ , together with each buyer's supplier roster and financing inputs, determines the bidding functions $\sigma_{ij}(c; \theta)$ that enter the moments below. We approximate these functions using an iterated best-response algorithm, which we describe in Section 5.3.

We estimate a preference parameter $\delta_{ij} > 0$ for each buyer–supplier pair. For a cost draw $c < \delta_{ij}$, supplier j submits its equilibrium quote $\sigma_{ij}(c; \theta)$. It wins when every rival k quotes more than $\sigma_{ij}(c; \theta) + \delta_{ik} - \delta_{ij}$ or abstains. Independent cost draws therefore give supplier j 's probability of winning conditional on cost c :

$$P_{ij}(c; \theta) = \prod_{k \in J_i \setminus \{j\}} \left[1 - F_{ik} \left(\sigma_{ij}^{-1}(c; \theta) + \delta_{ik} - \delta_{ij}; \theta \right) \right]. \quad (12)$$

Here F_{ik} denotes rival k 's marginal-cost distribution, and σ_{ik}^{-1} maps its quote threshold into a cost cutoff. Averaging $P_{ij}(c; \theta)$ over supplier j 's cost draws gives its unconditional winning share $s_{ij}^M(\theta)$.²⁰

$$s_{ij}^M(\theta) = \int_0^{\delta_{ij}} P_{ij}(c; \theta) dF_{ij}(c; \theta). \quad (13)$$

We compute the first two moments of prices conditional on supplier j winning using the same cost draws and winning probabilities:

$$m_{r,ij}^M(\theta) = \frac{1}{s_{ij}^M(\theta)} \int_0^{\delta_{ij}} \sigma_{ij}(c; \theta)^r P_{ij}(c; \theta) dF_{ij}(c; \theta), \quad r = 1, 2. \quad (14)$$

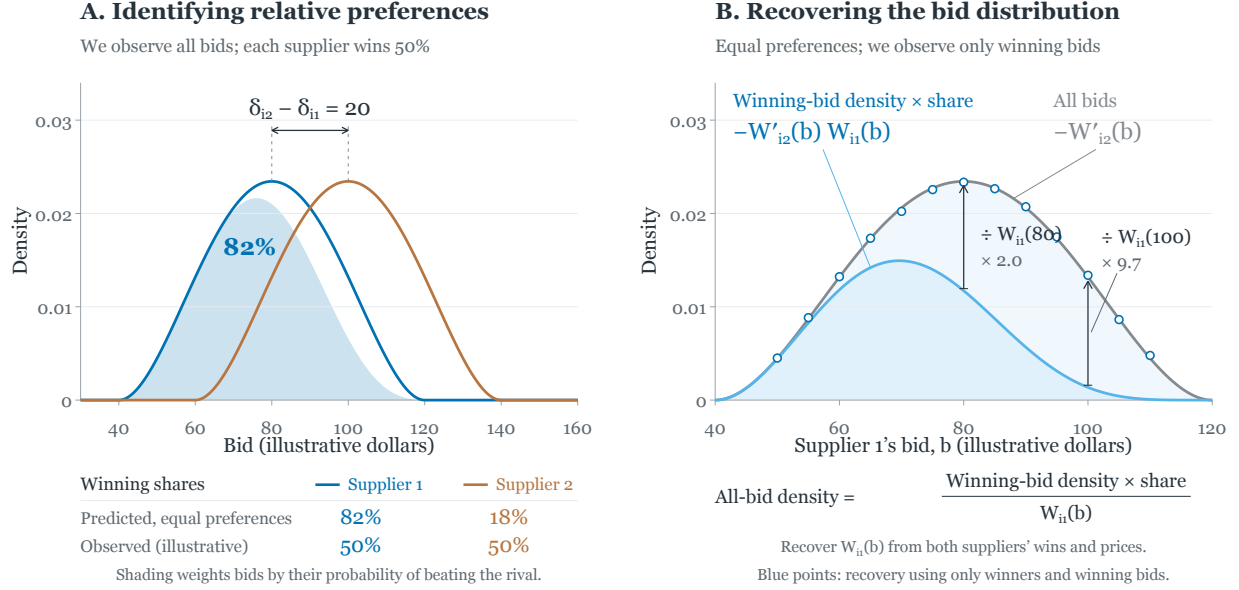
We weight each quote or its square by $P_{ij}(c; \theta)$ before averaging over costs. Dividing by $s_{ij}^M(\theta)$ conditions on supplier j winning. The first moment gives the mean transaction price, and $m_{2,ij}^M(\theta) - [m_{1,ij}^M(\theta)]^2$ gives its variance.

We do not estimate any interest rates r_{ij} , we simply recover them from the data. We do this for Loan and Factoring rates (Appendix C.2). The model's financing adjustment implies that $F_{ij}(\cdot; \theta)$ is Weibull with scale $\lambda_{ij} = \lambda_{g(i,j)}^C / (1 - r_{ij})$ and shape $\kappa_{g(i,j)}$. We also supply each buyer's outside share $\hat{s}_{i0}$, which we construct separately. We hold these inputs fixed while estimating θ .

²⁰A supplier who gets a realized cost $c_{ija} = \delta_{ij}$ can only win without a loss by quoting its cost, $\sigma_{ij}(\delta_{ij}; \theta) = \delta_{ij}$: a lower quote yields a loss if it wins, and a higher quote cannot win. Suppliers abstain above this cutoff, so independence gives

$$s_{i0}^M(\theta) = \prod_{j \in J_i} [1 - F_{ij}(\delta_{ij}; \theta)], \quad s_{i0}^M(\theta) + \sum_{j \in J_i} s_{ij}^M(\theta) = 1.$$

Figure 4: Identification



Notes: Independent illustrative bid draws; both suppliers always bid and the buyer always purchases. In panel B, equal preferences imply that $-W'_{i2}(b)$ gives supplier 1's bid density.

5.2 Identification

In this subsection we show that suppliers' winning shares and conditional winning-bid distributions uniquely identify buyers' preferences and suppliers' marginal cost distributions under our model and distributional assumptions.²¹ That is, the moments uniquely identify the primitives.

To build intuition, suppose we observe all bids from two suppliers serving buyer i . Both suppliers always bid and the buyer always purchases from one of them. Under independence, the two bid distributions tell us how often each supplier submits the lower quote. Panel A of Figure 4 plots an example in which supplier 2's bid distribution has the same shape as supplier 1's but lies to its right. If the buyer values the suppliers equally, supplier 1 wins about 82% of purchases and supplier 2 wins about 18%. The blue shading weights supplier 1's bid density by the probability of beating its rival; its area gives this predicted share. Now suppose the buyer can value the suppliers differently, but we do not know which supplier it prefers or by how much. We observe the same two bid distributions, yet each supplier wins 50% of purchases. With equal preferences, supplier 2's higher quotes would give it only an 18% winning share. Its observed 50% share therefore tells us that the buyer prefers supplier 2

²¹Conditional on a transaction, the probability that supplier j wins with a bid at most p equals its winning share times its conditional winning-bid CDF at p . Thus these shares and conditional distributions contain the same information as the joint distribution of winners and winning bids.

enough to compensate for those higher quotes. To determine how much, consider the effective quotes that the buyer compares: bids net of preferences, $b - \delta_{ij}$. Supplier 2’s bid distribution lies \$20 to the right of supplier 1’s. A preference advantage of \$20 offsets this difference, bringing the two distributions of effective quotes on top of one another. Each supplier then has an equal probability of offering the lower effective quote, consistent with the observed 50–50 shares. Thus, the discrepancy between predicted and observed shares identifies the preference difference, $\delta_{i2} - \delta_{i1} = \20 .

Continuing the example, observing all bids also allows us to recover suppliers’ marginal cost distributions, in addition to the buyer’s relative preferences. Once we recover preferences as described in the previous paragraph, opponents’ bid distributions determine a supplier’s probability of winning at each quote, $W_{ij}(b)$, and how that probability changes with its quote, $W'_{ij}(b)$. The pricing first-order condition in Section 4.2 then gives the markup, $-W_{ij}(b)/W'_{ij}(b)$. Subtracting this markup from each bid recovers the corresponding marginal cost; applying this inversion across the bid distribution recovers the cost distribution. This is the inversion logic of [Guerre, Perrigne, and Vuong \(2000\)](#) (GPV), adapted to procurement with buyer preferences.

This example illustrates that recovering preferences and marginal cost distributions from full bid distributions and shares is straightforward. The difficulty we face is that we only observe the *winning* bids.

When we observe only winning bids, we must account for selection into winning before applying the cost inversion above. For this harder case, we rely on a prior result: [Athey and Haile \(2002, Theorem 6\)](#) show that winning prices and winner identities identify the underlying bid distributions in asymmetric first-price auctions with independent private values. Panel B of Figure 4 illustrates this result with two suppliers whom the buyer values equally. We observe only winning bids, so competition removes each supplier’s losing quotes from the data. The light-blue curve shows supplier 1’s conditional winning-bid density multiplied by its winning share. At each quote b , this curve retains the fraction $W_{i1}(b)$ of the underlying bid density. Dividing by $W_{i1}(b)$ recovers the gray curve, with a larger proportional correction at higher quotes. We recover these winning probabilities from both suppliers’ winning bids and shares. Whenever supplier 2 wins, its quote tells us that supplier 1’s unobserved bid must have been higher. Under independence, we combine these bounds with the bids we observe to reconstruct the bid distributions and hence the winning probabilities.²² The blue circles show the density we recover using only winners and winning bids. For given unequal preferences, we account for preference differences when translating a rival’s winning quote into a bound; the same correction then applies. We then use the cost inversion above to recover participating suppliers’ costs. We derive the selection correction, including abstention, in Appendix D.3.

²²Independence rules out unobserved shocks that move suppliers’ costs together within a purchase.

The formal proof of identification is in Appendix D. We show that winning shares and conditional winning-bid distributions uniquely identify buyers' preferences and suppliers' marginal cost distributions under our model and the Weibull assumption. The intuition is that equilibrium bids approach δ_{ij} as costs approach the participation cutoff. Since all rivals can abstain, supplier j can win with bids arbitrarily close to δ_{ij} , while quotes above δ_{ij} cannot win. The upper endpoint of its winning-bid distribution therefore identifies δ_{ij} . Given these preferences and the outside share, independence and optimal bidding identify each supplier's cost distribution up to δ_{ij} , including the probability of drawing a higher cost. Within the Weibull family, the distribution below this cutoff uniquely determines both its scale and shape, and hence the entire cost distribution. This population result uses full winning-bid distributions; our estimator uses their first two moments and pools cost parameters across relationships to improve precision.

5.3 Estimation Procedure

We estimate the model using suppliers' empirical winning shares, $\hat{s}_{ij}$, and the first two moments of prices conditional on each supplier winning, $\hat{m}_{1,ij}$ and $\hat{m}_{2,ij}$.²³ We construct each buyer's outside share, $\hat{s}_{i0}$, separately using monthly invoice spending, drawing inspiration from business-to-consumer demand applications. Appendix C.1 describes the sample and this construction.

We estimate all parameters jointly by GMM, combining differences in winning shares with weighted differences in winning-price moments:

$$\begin{aligned} \hat{\theta}_\alpha \in \arg \min_{\theta > 0} & \left\{ \alpha \sum_i \sum_{j \in J_i \cup \{0\}} \left[s_{ij}^M(\theta) - \hat{s}_{ij} \right]^2 \right. \\ & \left. + \sum_i \sum_{j \in J_i} \sum_{a \in \mathcal{A}_{ij}^w} \sum_{r=1}^2 \left[\frac{m_{r,ij}^M(\theta) - (B_{ia}^w)^r}{\hat{m}_{1,ij}^r} \right]^2 \right\}. \end{aligned} \quad (15)$$

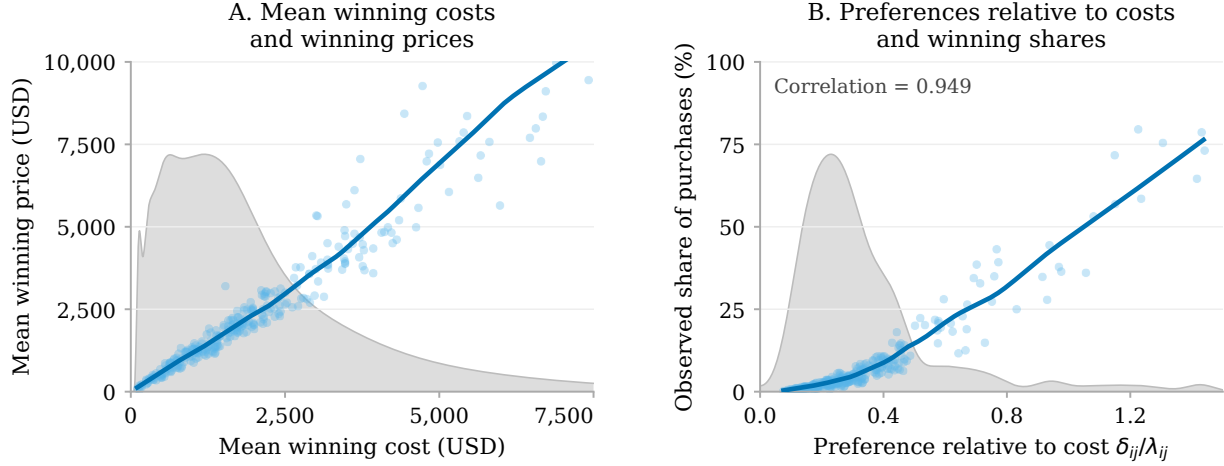
We sum over transactions, so each transaction contributes once.²⁴ We divide each price difference by the corresponding power of the relationship's average winning price to put the mean and second moment in comparable units. The parameter α controls the weight on shares relative to price moments. We match shares exactly, corresponding to the limiting case $\alpha \rightarrow \infty$.

For each candidate set of cost parameters, we recover the preferences that match empirical winning shares. Each preference trial requires approximating equilibrium bidding functions

²³For each buyer-supplier pair, $\hat{m}_{1,ij}$ is the average winning price and $\hat{m}_{2,ij}$ is the average squared winning price.

²⁴ $\mathcal{A}_{ij}^w$ contains buyer i 's purchases from supplier j , and B_{ia}^w denotes the transaction price in auction a .

Figure 5: Model Estimates



Notes: Points represent relationships; blue curves show local-linear fits and gray areas show densities on separate scales. Costs include financing; panel A omits eight relationships beyond its axis limits.

through iterated best responses and calculating the model moments. We then update the cost parameters to improve the fit of the price moments and repeat these calculations. Appendix C.4 describes the algorithm and convergence checks.

We compute standard errors that account jointly for sampling variation in winning shares and price moments. We assume that transactions are independent of each other and hold interest rate inputs and cost group assignments fixed. Appendix C.5 provides details.

5.4 Estimates

Our estimates imply a median own-price elasticity of -3.59 . Through the suppliers' pricing first-order condition, these elasticities imply a median markup of 39% over marginal cost, including financing.²⁵ Figure 5A compares estimated mean marginal costs conditional on winning with observed mean winning prices across buyer-supplier relationships. Appendix Table C.2 reports the cost-distribution parameters. Elasticities vary across winning transactions, with an interquartile range of -7.85 to -2.05 . For buyers with nine or fewer suppliers, the median elasticity equals -3.11 , compared with -3.88 for buyers with more than 9 suppliers. Median markups equal 47.4% for buyers with 9 or fewer suppliers and 34.8% for buyers with

²⁵At the median, a 1% increase in a supplier's quote lowers its probability of winning by approximately 3.59%, holding rivals' strategies fixed. Let $\varepsilon < 0$ denote this elasticity. At an interior optimum, the supplier's pricing first-order condition gives $(b - c)/b = -1/\varepsilon$ and hence $(b - c)/c = -1/(1 + \varepsilon)$, where b denotes the quote and c denotes marginal cost including financing. Thus, $\varepsilon = -3.59$ implies a margin of 28% and a markup over cost of 39%. Appendix C.6 gives the calculation and aggregation details for the three economic summaries in this subsection.

more than nine suppliers. For comparison, we calculate an aggregate accounting markup of 36% over variable expenses, including direct labor, using pooled data from Chile’s annual survey of road-freight firms for 2019–2023.²⁶ Appendix C.7 provides the calculation details. Coffey, McLaughlin, and Peretto (2026) estimate a markup of approximately 35% over marginal cost in their preferred specification for U.S. freight transportation.²⁷

On substitution between buying from an inside supplier and the outside option, our estimates imply a median elasticity of the probability of purchase with respect to financing-adjusted marginal costs of -0.56 , with an interquartile range of -0.68 to -0.47 . At the median, a 1% reduction in these costs across all suppliers increases purchases by approximately 0.56%, raising the share of potential orders that buyers complete from 89.0% to 89.4%. This represents a modest expansion of total purchases, bringing approximately 4.2% of previously forgone orders into the market. If a supplier increases their price, buyers can turn to another. They turn to the outside good only when none of their suppliers responds with a quote, this tends to be rare. The additional transactions generate the output-expansion effect in our counterfactuals. The associated welfare gain depends on both the number of new orders and the surplus each creates, as we will see in the next section.

On the trade-off between prices and supplier quality, we calculate buyers’ willingness to pay for additional quality. Specifically, we estimate a median compensating price elasticity, δ_{ij}/b , of 1.17 across model winning transactions, with an interquartile range of 1.07–1.33. At the median, a buyer would accept a 1.17% higher quote for a supplier it values 1% more, while retaining the same surplus.²⁸ To connect these valuations to purchasing patterns, Figure 5B compares preferences relative to financing-adjusted cost scales, δ_{ij}/λ_{ij} , with observed purchase shares. Suppliers with higher valuations relative to costs account for larger shares of their buyers’ purchases, meaning that suppliers with higher quality relative to costs get a larger share of the market.

5.5 Model Fit

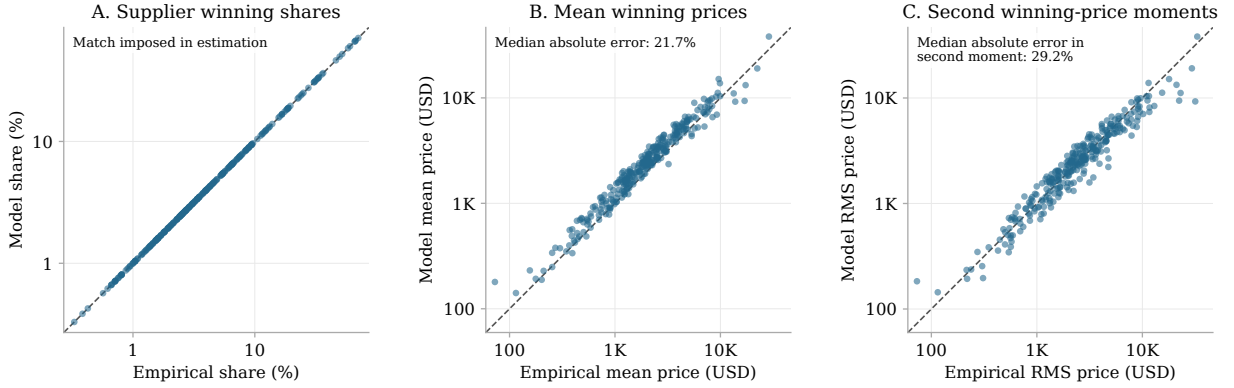
On the targeted moments: the model captures differences in winning prices across buyer–supplier relationships, but predicts higher mean prices than the data for most relationships. The average difference is 11.3%, giving each relationship equal weight. Figure 6 compares empirical supplier winning shares and the first two conditional winning-price moments with

²⁶The Instituto Nacional de Estadísticas (INE), Chile’s national statistics agency, conducts the *Encuesta Estructural de Transporte de Carga por Carretera* (ETRANC).

²⁷We refer to the preferred specification in the right-hand column of Table 3 and the authors’ discussion on page 17, where they report the implied markup.

²⁸Holding buyer surplus $u = \delta_{ij} - b$ fixed implies $db = d\delta_{ij}$ and hence $\frac{d \log b}{d \log \delta_{ij}} \Big|_u = \delta_{ij}/b$. We evaluate this elasticity using model winning prices.

Figure 6: Model Fit



Notes: Points represent buyer–supplier relationships; dashed lines mark equality. We impose exact share matching. Panel C plots square roots of second moments and reports errors for the raw moments.

their model counterparts for all 304 relationships. We impose exact share matching, while fitting the price moments with five group-specific cost scales and five group-specific shapes. Giving each relationship equal weight, we find median absolute percentage errors of 23.6% for mean winning prices and 42.4% for second moments. The model overpredicts mean prices for 59.9% of relationships, while second-moment errors fall on both sides of zero.

On the untargeted moments: the model captures the ordering of buyer–supplier relationships by their median and upper-quartile winning prices. Appendix Figure C.1 compares these quantiles with their empirical counterparts. Across the 304 relationships, the rank correlations equal 0.88 for medians and 0.92 for upper quartiles. For upper quartiles, the median absolute percentage error equals 22.7%. These patterns also hold within buyers: after removing buyer means from the log quantiles, the correlations equal 0.83 and 0.87, respectively.

We regress the estimated preference parameters $\hat{\delta}_{ij}$ on observable supplier characteristics for all 304 relationships (Appendix Table C.4). Comparing suppliers serving the same buyer and holding other characteristics fixed, buyers’ estimated willingness to pay is approximately \$600 higher per order for a supplier with twice the monthly billing to other customers, suggesting a premium associated with supplier scale. Buyers’ estimated willingness to pay is also lower for suppliers whose business with other customers relies more heavily on repeat transactions. One possible explanation is that these suppliers prioritize established customers, limiting their availability to the marginal buyer. Observable characteristics and measurement controls explain 15.9% of total preference variation; adding buyer fixed effects raises this fraction to 36.6%.

5.6 Limitations

Our current model does not include demand shocks, so buyers’ preferences remain fixed within each buyer–supplier relationship. We therefore attribute changes in supplier choice to costs and quotes, even though differences in project requirements may favor different suppliers. We have developed an extension that allows preferences to vary across projects and uses BLP-style instruments to identify the parameters governing these shocks. However, we have not yet overcome the computational challenges involved in estimating this extension reliably.

We also cannot separate common project-level cost shocks from suppliers’ private shocks with our current data and specification. Attributing common variation to private costs could inflate their estimated variance, overstate markups, and lower inferred marginal costs, as [Krasnokutskaya \(2011\)](#) finds in procurement auctions. To the extent that lower inferred costs reduce the gains we predict from cheaper financing, this could also lead us to understate factoring’s total effect. We regard this as a potential source of bias rather than an established direction for our counterfactual results.

6 Counterfactuals

In this section, we examine the welfare effects of factoring. We use our model to compare outcomes under the status quo, where firms can finance their operations through either factoring or bank loans, against a counterfactual in which factoring is unavailable. Our main finding is that factoring has a small positive effect on total welfare, reflecting two forces pushing in opposite directions. On the one hand, factoring lowers prices and expands output, increasing welfare. On the other, it reallocates production toward less efficient suppliers, reducing welfare.

6.1 Aggregate effects

We define the welfare generated by a B2B transaction as the buyer’s value from the purchase minus the supplier’s material production cost. Prices and interest rates determine how buyers, suppliers, and financial firms divide this surplus. We assume that financial firms incur no marginal resource costs.²⁹ Purchase and financing payments therefore transfer income among these parties without changing their combined surplus for a given transaction. We compare bank loans alone ($T = 0$) with access also to factoring ($T = 1$). Conditional on the full

²⁹More generally, the same welfare comparison holds if financial intermediaries incur identical aggregate resource costs in the equilibria with and without factoring, since those costs cancel when we take the difference.

material-cost vector $\mathbf{c}^{\text{prod}}$, supplier j wins with probability $s_{ij}^T(\mathbf{c}^{\text{prod}})$; its average over cost draws gives the unconditional share s_{ij}^T . Assigning zero welfare to no purchase, we obtain expected welfare per transaction opportunity:

$$W_i^T = \int \sum_{j \in J_i} s_{ij}^T(\mathbf{c}^{\text{prod}}) (\delta_{ij} - c_j^{\text{prod}}) dF_i^{\text{prod}}(\mathbf{c}^{\text{prod}}), \quad T \in \{0, 1\}.$$

We compare $\Delta W_i = W_i^1 - W_i^0$, holding buyer values and the joint material production-cost distribution F_i^{prod} fixed.

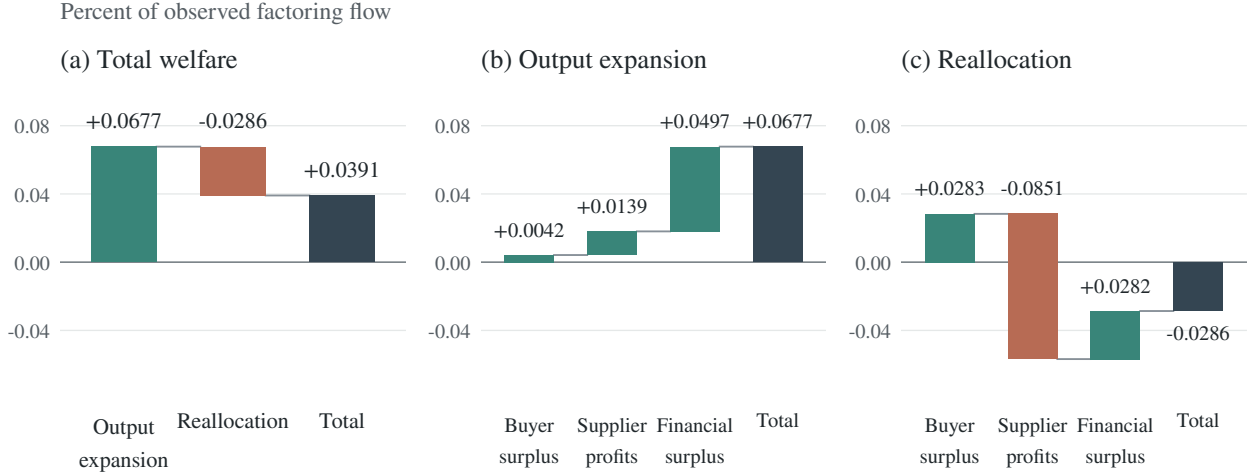
We distinguish the welfare effects relating to output expansion, reallocation, and transfers by comparing outcomes in the equilibria with and without factoring, holding the production-cost realization fixed. Output expansion captures each party's surplus from projects that proceed only with factoring. Reallocation captures each party's full change in surplus when a project proceeds in both equilibria but a different supplier wins. In both the expansion and reallocation categories, we calculate each party's surplus using the prices and financing payments in the corresponding equilibrium. When the same supplier wins in both equilibria, changes in prices and interest payments transfer surplus among buyers, suppliers, and financial firms without changing total welfare.

We estimate that access to factoring generates a net welfare gain equivalent to 0.038% of total factoring volume. Lower financing costs allow suppliers to offer prices at which previously unviable projects can proceed, generating an output expansion gain of 0.075% of factoring flow. Financing relief differs across suppliers, however, so firms can become more competitive without generating more buyer value net of production costs. In our estimates, the resulting reallocation raises production costs by more than it raises buyer value, reducing welfare by 0.0370% of factoring flow. This loss offsets about 49% of the gains from additional trade: factoring expands production, but its uneven financing benefits also shift existing production toward less efficient suppliers.

Lower financing costs make additional projects viable and expand output, but these projects generate only modest welfare gains. The number of completed projects increases by 0.67% relative to the equilibrium without factoring. These additional projects generate total buyer value³⁰ equal to 1.3738% of the total volume factored. However, they incur material production costs equal to 1.2988% of that volume, leaving a welfare gain of only 0.0750%. This narrow gap between buyer value and production costs explains why these projects disappear without factoring: higher financing costs prevent suppliers from covering their costs at prices buyers will accept. Even with factoring, suppliers must charge prices close to buyers' valuations, so buyers retain very little surplus. Indeed, buyers receive only

³⁰The sum of their δ_{ij} valuations.

Figure 7: Output expansion, reallocation, and total welfare



Notes: Values express welfare contributions as percentages of observed factoring flow. Buyer surplus equals value minus price; supplier profits equal revenue net of production and financing costs; financial-sector surplus equals financing receipts. Floating bars show contributions; dark bars show totals. Totals use unrounded values.

6.8% of the resulting surplus, suppliers receive 19.8%, and the financial sector receives 73.4% through interest payments. Financial firms earn interest on invoice payments, so these projects generate financing revenue even when they leave buyers and suppliers with little surplus.

An efficient allocation of production assigns each project to the supplier who creates the most buyer value net of material production costs. Buyers, however, choose suppliers based on value net of price. So differences between prices and costs can lead to an inefficient allocation of production. In our setting, two wedges separate prices from material costs: a markup and a financing wedge. We find that markups account for about 90% of the aggregate gap between prices and material costs. We also find that markups and financing wedges have a within-buyer correlation of -0.558 when we express both as shares of buyer value. This negative correlation shows that suppliers with lower markup shares tend to face higher financing burdens relative to buyer value. These opposing wedges can partly offset each other, so lowering financing costs need not improve the allocation of existing production.

Factoring's reallocation effect reduces total welfare by shifting projects toward suppliers who create less surplus on average. On projects that change suppliers between the two equilibria, the new winners face average loan rates of 6.73% over the invoice payment term, compared with 5.07% for the suppliers they replace. Factoring lowers these rates by an average of 2.30 percentage points for new winners and 0.85 percentage points for the displaced suppliers. The new winners offer higher buyer value and charge lower markups in the

factoring equilibrium, but their higher production costs more than offset the additional value. They therefore generate 3.1% less value net of material production costs on average than the suppliers they replace. Without factoring, their higher borrowing costs partly offset the competitive advantage of their lower markups. Factoring eases this financing disadvantage, allowing them to win projects from rivals who create more surplus. In the aggregate, reallocation raises production costs by more than it raises buyer value, reducing welfare by 0.0286% of the total volume factored (Figure 7(c)).

6.2 Redistribution of welfare

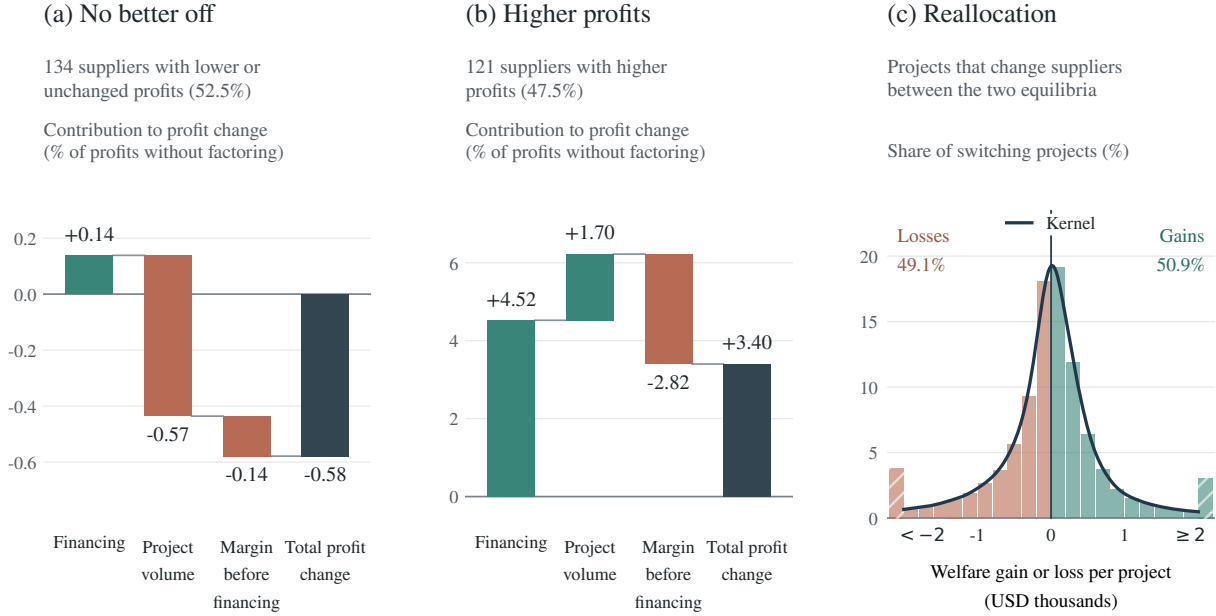
Factoring redistributes substantially more surplus than it creates. Buyers gain surplus equivalent to 0.79% of the total volume factored, and suppliers' profits after financing rise by 1.22% of that volume. Financial-sector surplus falls by 1.98% of the total volume factored. This reduction accounts for almost all of the combined gains to buyers and suppliers, with the increase in total surplus contributing only 0.038% of that volume.

The largest surplus transfer is from the financial sector to suppliers, in the form of lower debt interest payments. On projects where the same supplier wins in both equilibria, this transfer amounts to 2.05% of the total volume factored. Suppliers pass on 0.76% of the total volume factored to buyers through lower prices, or the equivalent of about 38% of their total financing savings. The aggregate increase in supplier profits conceals substantial differences across firms because factoring reduces their financing costs unevenly.

Redistribution across suppliers. Most suppliers are worse off in the equilibrium with factoring, even though overall seller surplus increases. Most suppliers lose because the competitive pressure from rivals' financing savings outweighs the benefits of their own financing relief. Factoring leaves financing rates unchanged for 37% of suppliers. Among these suppliers, 95% earn lower profits after financing in the equilibrium with factoring. Only 38% of all suppliers receive an average rate reduction greater than half a percentage point. Suppliers with larger reductions can lower prices and win business from their rivals, intensifying competition for those who receive little relief. As Section 4.2 explains, stronger competition can make suppliers' probability of winning more sensitive to price, putting downward pressure on markups. Figure 8(a) shows the suppliers whose profits fall or remain essentially unchanged: as a group, they lose market share, and changes in margins before financing further reduce their profits. Their limited financing savings cannot offset these losses.

A minority of suppliers do see their profits increase in an equilibrium with Factoring, relative to an equilibrium with only loans. These sellers benefit from substantial reductions

Figure 8: Supplier profits and welfare effects of reallocation



Notes: Panels (a)–(b). We explain how access to factoring changes total supplier profits after financing. Each contribution is a percentage of the group’s total profits without factoring. Financing combines the effect of lower rates with changes in the cost of financing production. Project volume captures gains or losses from more or fewer projects. Margin before financing captures changes in price minus material cost per project, net of associated financing payments. The dark bar sums the three contributions. Vertical scales differ.

Panel (c). We compare projects that change suppliers, using the same production-cost draws. The horizontal axis shows buyer value minus material cost under the winner with factoring, less that under the winner with bank loans only. Negative values indicate welfare losses. Bars show project shares using fixed buyer weights and USD 200 intervals; the kernel curve smooths this distribution. Hatched bars pool each tail beyond the displayed range.

in interest payments, and financing relief contributes 4.52 percentage points to the group’s profit growth, the largest positive component in Figure 8(b). Lower financing costs allow them to reduce prices and gain market share while retaining enough of the savings to earn more per project after covering production and financing costs. The decline in margins before financing offsets 2.88 percentage points of the financing gain, leaving a 1.65-percentage-point contribution from higher net profits per project. Additional projects contribute a further 1.66 percentage points, so the two sources contribute roughly equally to the group’s 3.31% increase in total profits after financing. These gains outweigh the losses among other suppliers, so aggregate seller surplus rises even though most suppliers lose. Our comparison measures the effect of market-wide access to factoring, so suppliers can lose when their rivals obtain cheaper financing.

7 Conclusion

In business-to-business markets, buyers often pay a month or more after delivery, meaning the seller must make a loan to the buyer for the duration. Trade credit therefore creates a gap between the nominal payment a buyer makes and the amount the supplier retains after financing this loan to the buyer. The size of this gap depends on the payment delay and the interest rate the supplier pays. Longer delays and higher borrowing rates reduce the value of a given nominal payment, so the same payment terms can impose different burdens on competing suppliers. These differences affect the prices suppliers can offer and the business they win. Factoring can narrow these differences by allowing suppliers to finance invoices using their buyers' credit rating rather than the suppliers' own.

Our main finding is that factoring has a small positive effect on total welfare, reflecting two opposing forces. On the one hand, lower financing costs allow suppliers to offer prices that make additional transactions viable, increasing welfare. On the other hand, uneven financing relief changes suppliers' relative competitiveness and shifts existing business across them. In our estimates, this reallocation raises production costs by more than it raises buyer value, reducing welfare. Additional trade increases welfare by 0.075% of the total volume factored, while reallocation reduces it by 0.037%, leaving a net gain of 0.038%.

Beyond its effect on total welfare, factoring has large redistributive effects. Lower interest payments transfer surplus from the financial sector to the real economy. Financial firms lose interest revenue equivalent to 1.98% of the total volume factored, while buyers and suppliers together gain surplus equivalent to 2.02% of that volume. Suppliers in turn transfer surplus equivalent to 0.76% of that volume to buyers through lower prices. Although aggregate supplier surplus increases, more than half of suppliers earn lower profits in the equilibrium with factoring. Only a minority receive substantial financing relief. Most receive little or none, yet face stronger competition from rivals whose larger financing savings allow them to lower prices and win business. Factoring therefore generates large gains for a minority of suppliers, while most gain nothing or lose.

Our analysis highlights how improving financial access of firms and reducing financial costs does not necessarily need to improve welfare. When financing costs partly offset differences in markups, reducing one distortion can worsen allocation. Evaluating credit access therefore requires measuring which suppliers gain business and which they displace, alongside the gains from additional trade. Allowing dynamics such as entry, investment, and lenders' pricing responses would extend this comparison to longer-run effects.

References

- Allen, J., R. Clark, and J.-F. Houde (2019, August). Search Frictions and Market Power in Negotiated-Price Markets. *Journal of Political Economy* 127(4), 1550–1598.
- Amberg, N., T. Jacobson, and Y. Qi (2024, May). Supply-Chain Finance: An Empirical Evaluation of Supplier Outcomes. Working Paper 435, Sveriges Riksbank.
- Susan Athey and Philip A. Haile. Identification of Standard Auction Models. *Econometrica*, 70(6):2107–2140, November 2002. URL <https://cpb-us-w2.wpmucdn.com/campuspress.yale.edu/dist/8/4126/files/2022/08/athey-haile-ema.pdf>.
- Banerjee, A. V. and E. Duflo (2014, April). Do Firms Want to Borrow More? Testing Credit Constraints Using a Directed Lending Program. *The Review of Economic Studies* 81(2), 572–607.
- Beckert, W., H. Smith, and Y. Takahashi (2026, June). Competition in a Spatially Differentiated Product Market with Negotiated Prices. *The Review of Economic Studies*. Advance online publication.
- Berry, S., J. Levinsohn, and A. Pakes (1995, July). Automobile Prices in Market Equilibrium. *Econometrica* 63(4), 841–890.
- Brown, J. D. and J. S. Earle (2017). Finance and growth at the firm level: Evidence from SBA loans. *The Journal of Finance* 72(3), 1039–1080.
- Cai, J. and A. Szeidl (2024, August). Indirect Effects of Access to Finance. *American Economic Review* 114(8), 2308–2351.
- Bentley Coffey, Patrick A. McLaughlin, and Pietro F. Peretto. Regulation and the cost of moving goods. Economics Working Paper 26108, Hoover Institution, March 2026. URL <https://www.hoover.org/sites/default/files/research/docs/26108-McLaughlin-Coffey-Peretto.pdf>.
- Cuesta, J. I. and A. Sepulveda (2021, September). Price Regulation in Credit Markets: A Trade-Off between Consumer Protection and Credit Access.
- Figal Garone, L., V. Luca, R. Stucchi, and J. Tessada (2026, May). The impact of reverse factoring on MSMEs: Firm-level evidence from Mexico. Development through the Private Sector Series, Technical Note 51, IDB Invest.

- Guerre, E., I. Perrigne, and Q. Vuong (2000, May). Optimal Nonparametric Estimation of First-Price Auctions. *Econometrica* 68(3), 525–574.
- Kastl, J., E. Richert, and J. Rüdiger (2025). Efficient Grid Search to Solve Static Games with Private Information. Marketing data center paper, Kilts Center at Chicago Booth.
- Klapper, L. (2006, November). The role of factoring for financing small and medium enterprises. *Journal of Banking & Finance* 30(11), 3111–3130.
- Elena Krasnokutskaya. Identification and estimation of auction models with unobserved heterogeneity. *The Review of Economic Studies*, 78(1):293–327, 2011. URL <https://www.econ2.jhu.edu/people/Krasnokutskaya/Restud004.pdf>.
- Maskin, E. and J. Riley (2003). Uniqueness of equilibrium in sealed high-bid auctions. *Games and Economic Behavior* 45, 395–409.
- McKelvey, R. D. and T. R. Palfrey (1995). Quantal response equilibria for normal form games. *Games and Economic Behavior* 10(1), 6–38.
- Aviv Nevo. Measuring Market Power in the Ready-to-Eat Cereal Industry. *Econometrica*, 69(2):307–342, 2001. doi: 10.1111/1468-0262.00194. URL <https://doi.org/10.1111/1468-0262.00194>.
- Orestes, V., T. Silva, and H. Zhang (2025, November). Corporate Liquidity Supply from Non-Bank Intermediaries and the Real Effects of Factoring. Working paper.
- Pinkse, J. and K. Schurter (2023, May). Estimation of auction models with shape restrictions. Working paper.
- Reny, P. J. and S. Zamir (2004). On the existence of pure strategy monotone equilibria in asymmetric first-price auctions. *Econometrica* 72, 1105–1125.
- Rotemberg, M. (2019, October). Equilibrium Effects of Firm Subsidies. *American Economic Review* 109(10), 3475–3513.
- Salz, T. (2022, February). Intermediation and Competition in Search Markets: An Empirical Case Study. *Journal of Political Economy* 130(2), 310–345.

A Reduced-Form Supporting Results

A.1 Full IV Results

Table 2 reports month-five effects, their main HC0 Wald intervals, Fieller sets, and the number of complete supplier pairs. Table 3 reports the score-adjusted intervals and compares the two sets of p -values. Figures 9 and 10 show all 19 outcome profiles, with main HC0 whiskers. Each first stage uses 25,468 suppliers. Outcome sample size can change across horizons when the underlying measure is missing. The existing-buyer billing and rate measures use buyers whose first observed transaction occurs by month zero. The rival-billing measure sums rivals' sales to the supplier's current buyers when the rival also served that buyer in the preceding calendar month. Neither definition uses the fixed month-1 buyer set that defines our buyer-absence indicator.

Table 2: First-difference IV effects at month five

Outcome	Effect	HC0 95% Wald	HC0 95% Fieller	N
Any ceding to Factor X	+42.22	[12.04, 72.39]	[14.28, 82.59]	25,468
Any ceding to any assignee	+39.24	[-2.39, 80.87]	[-3.32, 89.69]	25,468
Total billing	+1.71	[-1.46, 4.89]	[-1.84, 5.13]	12,748
Sales to buyers absent in month -1	+1.16	[0.27, 2.05]	[0.32, 2.29]	12,748
Billing to buyers known by month 0	+1.20	[-1.79, 4.20]	[-2.22, 4.36]	12,748
Number of invoices	+0.72	[-1.69, 3.13]	[-2.08, 3.22]	12,748
Number of buyers	+1.34	[-0.53, 3.20]	[-0.67, 3.43]	12,748
Average invoice value	+1.60	[-0.22, 3.43]	[-0.26, 3.74]	12,748
Rival billing: prior-month links	+1.12	[-3.46, 5.70]	[-3.95, 6.11]	12,748
Buyer sales-size index	+0.03	[-0.04, 0.10]	[-0.04, 0.11]	6,364
Billing share: micro buyers	+0.02	[-0.41, 0.45]	[-0.46, 0.49]	12,748
Billing share: small or micro buyers	+0.38	[-0.33, 1.09]	[-0.37, 1.19]	12,748
Billing share: medium or large buyers	+0.68	[-0.20, 1.55]	[-0.21, 1.73]	12,748
Billing share: large buyers	+0.20	[-0.59, 0.99]	[-0.66, 1.08]	12,748
Billing share: unknown buyer size	+0.24	[-0.17, 0.65]	[-0.18, 0.72]	12,748
Buyer purchases from competitors	-0.35	[-0.79, 0.09]	[-0.86, 0.10]	11,707
Buyer purchases from supplier	+0.35	[-0.09, 0.79]	[-0.10, 0.86]	11,707
Average list factoring rate	+0.77	[-0.14, 1.68]	[-0.07, 1.94]	119
List rate: buyers known by month 0	+0.67	[-0.26, 1.60]	[-0.22, 1.84]	115

Notes: Both interval columns use joint HC0 covariance, conditional on estimated leniency, and retain covariance between stages. Ceding effects use a 0-to-1 change in any approval; all other effects use a 1.4-percentage-point increase in approval share. We report probabilities, shares, and rates in percentage points; log outcomes in 100 times log points; and buyer size in index points. N counts supplier pairs, not supplier-month observations. The rate samples contain only 119 pairs overall and 115 for buyers known by month zero; these selected samples and the common-slope assumption limit the rate estimates' interpretation.

Table 3: Sensitivity to estimated-leniency uncertainty at month five

Outcome	Score 95% Wald	Score 95% Fieller	HC0 p	Score p
Any ceding to Factor X	[4.57, 79.86]	[7.77, 104.66]	0.006	0.028
Any ceding to any assignee	[-13.37, 91.85]	[-18.35, 112.18]	0.065	0.144
Total billing	[-2.37, 5.79]	[-3.52, 6.32]	0.291	0.411
Sales to buyers absent in month -1	[0.03, 2.30]	[0.12, 2.94]	0.010	0.044
Billing to buyers known by month 0	[-2.58, 4.99]	[-3.83, 5.32]	0.431	0.534
Number of invoices	[-2.36, 3.81]	[-3.52, 3.96]	0.557	0.647
Number of buyers	[-0.97, 3.64]	[-1.37, 4.17]	0.161	0.255
Average invoice value	[-0.72, 3.93]	[-0.89, 4.74]	0.084	0.176
Rival billing: prior-month links	[-4.61, 6.85]	[-6.00, 7.79]	0.632	0.702
Buyer sales-size index	[-0.06, 0.12]	[-0.06, 0.15]	0.396	0.507
Billing share: micro buyers	[-0.54, 0.58]	[-0.67, 0.68]	0.927	0.944
Billing share: small or micro buyers	[-0.50, 1.27]	[-0.59, 1.55]	0.289	0.396
Billing share: medium or large buyers	[-0.42, 1.77]	[-0.48, 2.16]	0.130	0.225
Billing share: large buyers	[-0.80, 1.21]	[-1.01, 1.40]	0.618	0.693
Billing share: unknown buyer size	[-0.25, 0.72]	[-0.27, 0.90]	0.258	0.337
Buyer purchases from competitors	[-0.91, 0.21]	[-1.09, 0.25]	0.117	0.218
Buyer purchases from supplier	[-0.21, 0.91]	[-0.25, 1.09]	0.117	0.218
Average list factoring rate	[-1.01, 2.55]	[-1.02, 3.34]	0.096	0.398
List rate: buyers known by month 0	[-1.23, 2.57]	[-1.30, 3.33]	0.161	0.492

Notes: Score intervals use supplier influence functions that account for estimation of leniency and covariance between stages. The final columns compare main HC0 and score-adjusted Wald p -values. Point estimates, samples, and reporting contrasts match Table 2: a 0-to-1 change in any approval for ceding and the exact calibrated 1.4-percentage-point approval-share contrast for all other outcomes. Units match that table.

Figure 9: First-difference IV profiles: outcomes 1–10

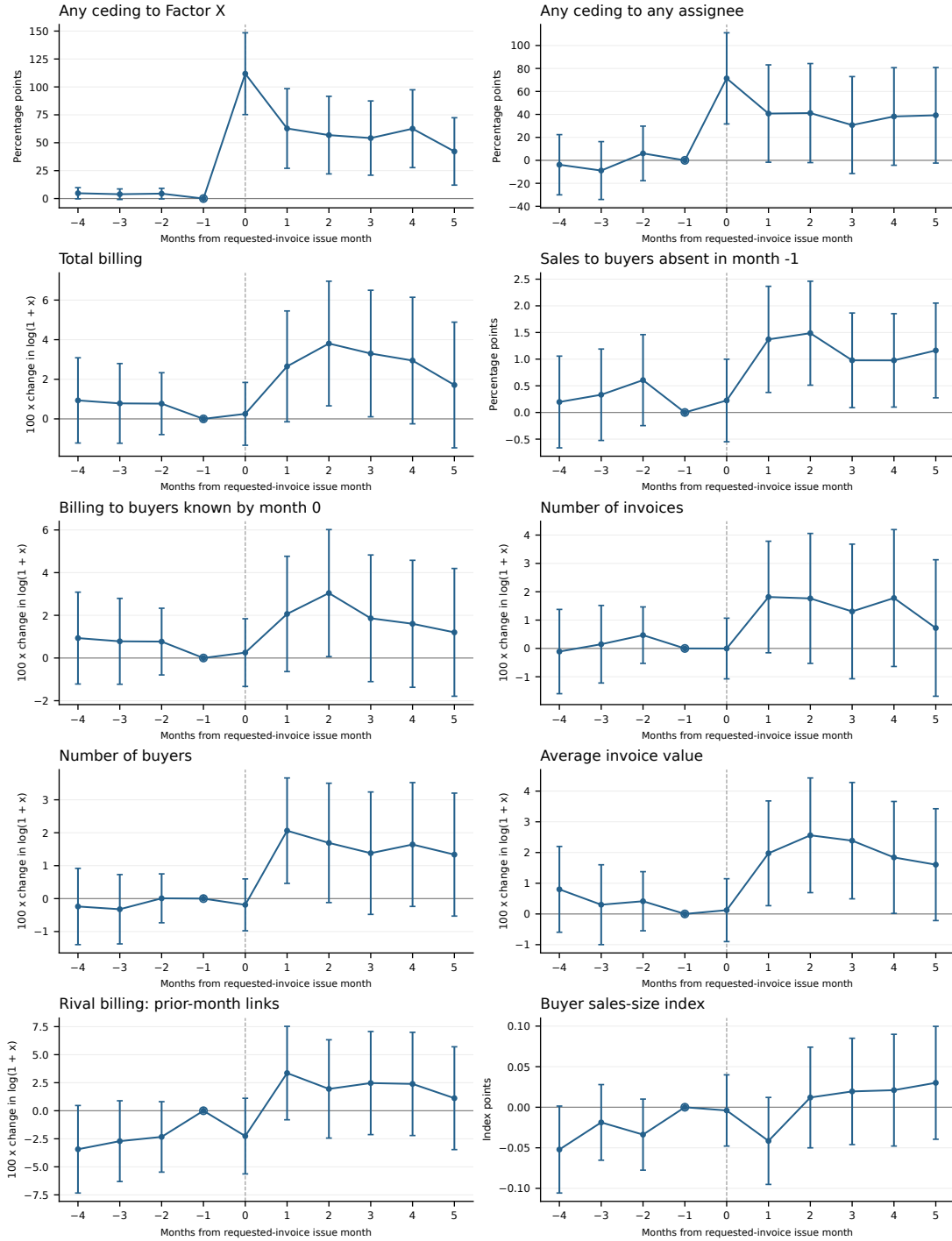
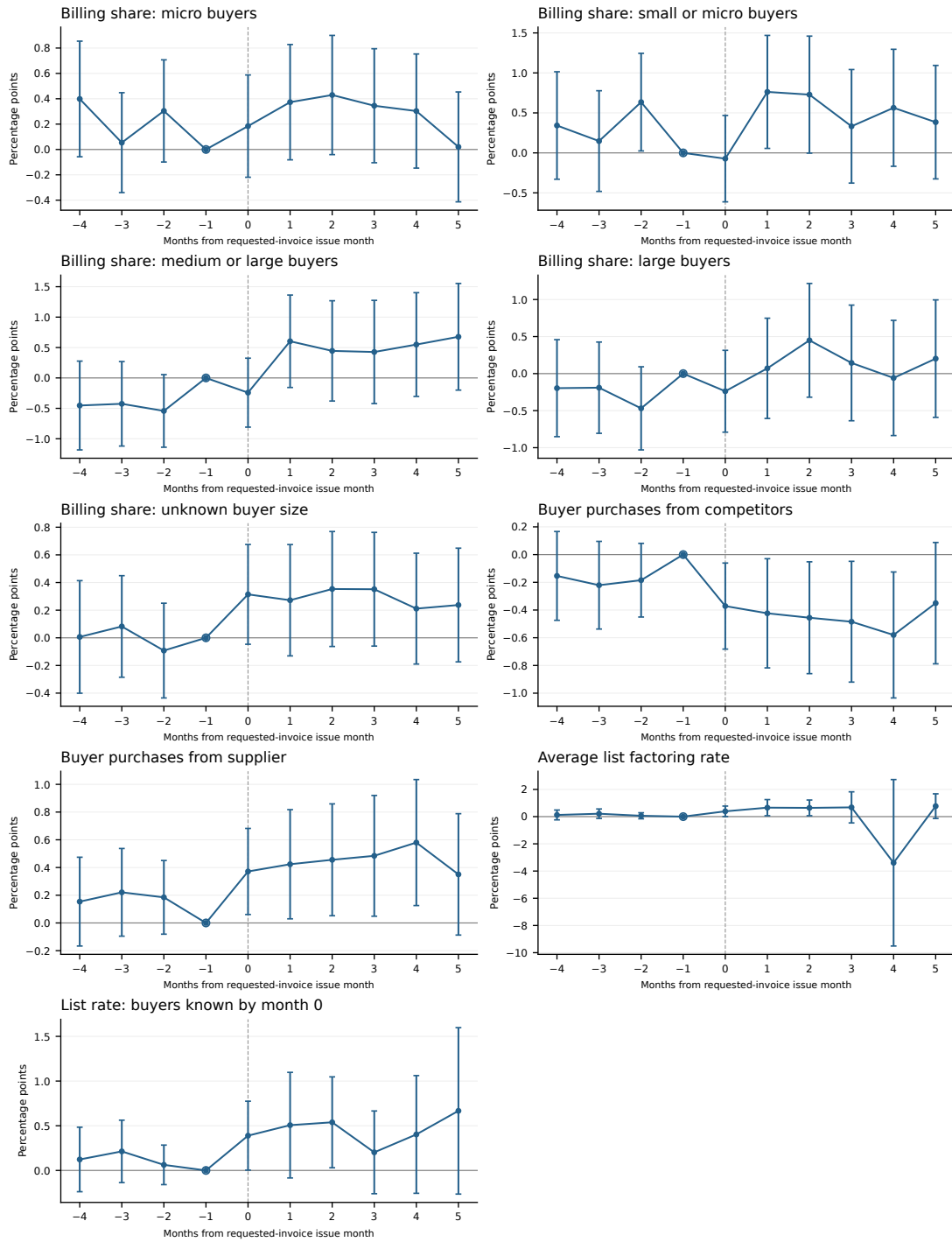


Figure 10: First-difference IV profiles: outcomes 11–19



A.2 Balance Across Risk Officers

We test whether initial risk officers receive applicants with different pre-application characteristics. For each outcome, we estimate

$$Y_j^{\text{pre}} = \alpha + \sum_{r \neq r_0} \theta_r \mathbf{1}\{r(j) = r\} + \mu_{m(j)} + e_j,$$

where Y_j^{pre} denotes supplier j 's average outcome over months -6 through -1 , $r(j)$ denotes its initial officer, r_0 denotes the reference officer, and $m(j)$ denotes its application month. We include application-month fixed effects $\mu_{m(j)}$ and test the joint null that all officer coefficients θ_r , $r \neq r_0$, equal zero, using heteroskedasticity-robust HC1 covariance.

Table 4 reports the tests for suppliers with an observed initial officer. We cannot reject equality across officers at the 5% level for any of the 24 outcomes. The smallest p -value is 0.055, for log average invoice value. These results support comparability in observed characteristics within application months; they do not establish random assignment or the exclusion restriction.

Table 4: Balance in Supplier Characteristics Across Risk Officers

Outcome	Suppliers	Officer F-stat.	Officer p-value
Log average invoice value	12,748	1.80	0.055
Share billing to small-or-smaller buyers	12,748	1.73	0.068
Average invoice value	12,748	1.68	0.080
Buyer size index	12,668	1.63	0.092
Share billing to medium-plus buyers	12,748	1.54	0.118
Log total billing	12,748	1.35	0.198
Log old-client billing	12,748	1.35	0.198
Share billing to large buyers	12,748	1.31	0.218
Old-client billing	12,748	1.17	0.302
Total billing	12,748	1.17	0.302
Share billing to micro buyers	12,748	1.05	0.399
Own share at buyers	12,748	1.04	0.402
Share billing to unknown-size buyers	12,748	0.99	0.446
Log rival billing	12,748	0.93	0.506
Avg. imputed factoring rate, old clients	152	0.65	0.735
Avg. imputed factoring rate	152	0.65	0.735
Share billing ceded	12,748	0.67	0.750
Competitor share at buyers	12,748	0.65	0.770
Any ceded invoice	12,748	0.49	0.900
Rival billing	12,748	0.43	0.934
Distinct clients	12,748	0.35	0.968
Log distinct clients	12,748	0.28	0.985
Number of invoices	12,748	0.26	0.989
Log number of invoices	12,748	0.24	0.992

Notes: Each row reports the joint test of initial risk-officer indicators in a regression of the pre-request outcome on officer fixed effects and assignment-month fixed effects. The table includes every estimated balance outcome with a valid officer-test p-value and is sorted by p-value. The p-value tests only officer indicators, not the month fixed effects.

A.3 Direct Reduced Forms

The following figures report $\hat{\delta}_h$, the effect of leniency on the outcome change before dividing by the first-stage slope. Each panel scales leniency by 10 percentage points. Whiskers show main HC0 95 percent Wald intervals. Table 5 uses the joint covariance across the three pre-reference horizons. The officer sensitivity uses a small-sample-adjusted clustered covariance and an F reference distribution; the main HC0 and supplier score-adjusted tests use a chi-squared reference distribution.

Table 5: Joint tests of pre-reference reduced-form coefficients

Outcome	HC0 W	HC0 p	Score p	Officer p
Any ceding to Factor X	4.81	0.186	0.408	0.004
Any ceding to any assignee	2.02	0.567	0.716	0.036
Total billing	1.25	0.741	0.856	0.030
Sales to buyers absent in month -1	2.23	0.527	0.710	0.162
Billing to buyers known by month 0	1.25	0.741	0.856	0.030
Number of invoices	1.26	0.739	0.847	0.106
Number of buyers	0.52	0.914	0.955	0.888
Average invoice value	1.66	0.646	0.789	0.010
Rival billing: prior-month links	3.92	0.270	0.484	0.003
Buyer sales-size index	5.07	0.167	0.319	0.004
Billing share: micro buyers	5.72	0.126	0.314	0.000
Billing share: small or micro buyers	5.74	0.125	0.304	0.000
Billing share: medium or large buyers	3.84	0.280	0.476	0.000
Billing share: large buyers	3.15	0.368	0.549	0.011
Billing share: unknown buyer size	0.98	0.806	0.886	0.004
Buyer purchases from competitors	2.84	0.416	0.623	0.111
Buyer purchases from supplier	2.84	0.416	0.623	0.111
Average list factoring rate	2.53	0.470	0.819	0.223
List rate: buyers known by month 0	2.53	0.470	0.819	0.223

Notes: The null sets the reduced-form coefficients at $-4, -3, -2$ jointly to zero. HC0 W is the main conditional Wald statistic. The p -value columns use main HC0 inference, score-adjusted supplier inference, and score-adjusted officer clustering. The tests concern the selected FD specification and do not establish the identifying assumptions.

Figure 11: Direct reduced-form profiles: outcomes 1–10

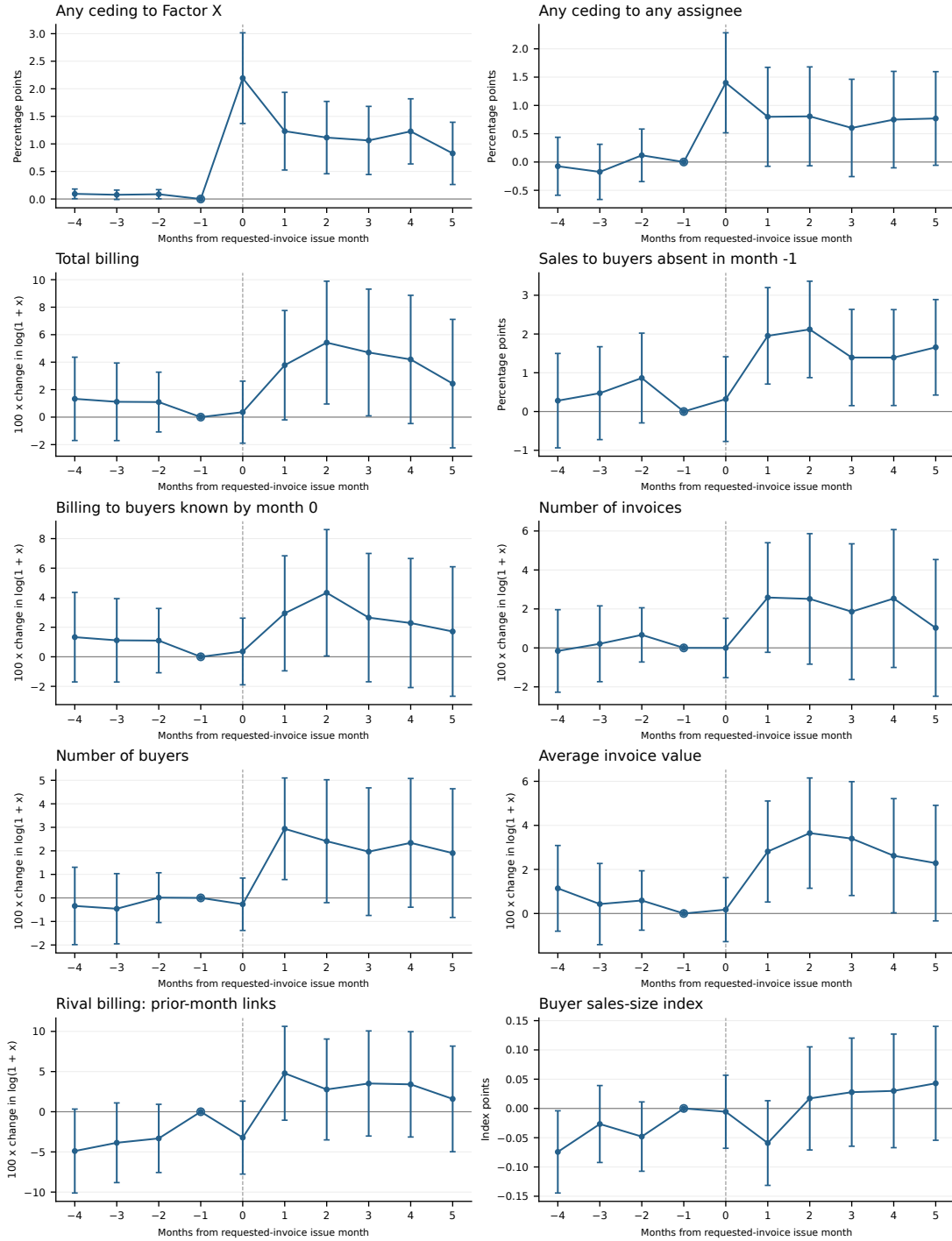
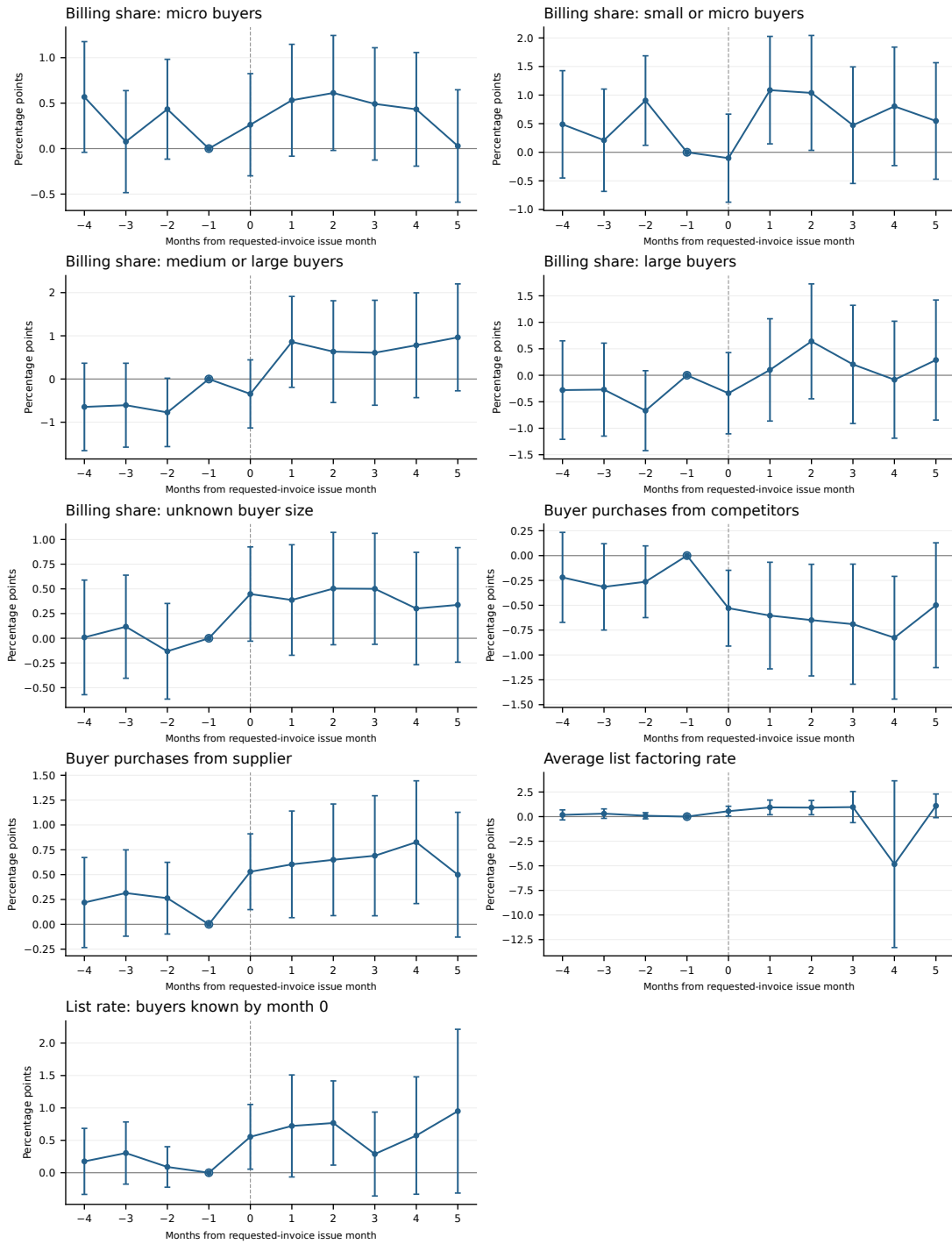


Figure 12: Direct reduced-form profiles: outcomes 11–19



A.4 First-Stage Estimates

Table 6: Common first stage and calendar-control sensitivity

Calendar controls	Treatment	Slope	HC0 SE	HC0 F	Score SE	Score F
Invoice cohort	Approval share	0.1999	0.0421	22.58	0.0566	12.46
Invoice cohort	Any approval	0.1961	0.0440	19.91	0.0584	11.26
Application month	Approval share	0.0986	0.0472	4.36	0.0703	1.97
Application month	Any approval	0.0895	0.0489	3.36	0.0711	1.59

Notes: Every row uses 25,468 suppliers and a common slope with billing-group by calendar-cell intercepts. The main model uses invoice-event cohorts. Application-month rows change only the first-stage calendar controls as a diagnostic. HC0 treats leniency as observed; score inference accounts for its estimation. Each F equals the squared slope-to-standard-error ratio for the corresponding covariance estimator.

A.5 IV Estimation and Inference

Outcome changes and samples. We index suppliers by j and event months by h . Month zero is the earliest issue month among the invoices that a supplier submits in its initial application window. It need not equal the application month. Let $c(j)$ denote this invoice-event calendar cohort and define $\Delta_h Y_j = Y_{jh} - Y_{j,-1}$, for $h \in \{-4, \dots, 5\}$. Differencing removes time-invariant supplier levels. We normalize the entire month- -1 response to zero.

The broad first-stage sample $\mathcal{B}$ contains 25,468 suppliers with initial approval and eligible leniency observations. For the two ceding probability outcomes, we use this broad sample in both stages and define A_j as an indicator that Factor X approves at least one initial invoice. For the other 17 outcomes, we define A_j as the fraction of initial invoices that X approves and restrict the outcome sample to suppliers with at least USD 200 in billing in months 0, -1 , and -2 . This restriction gives us 12,748 established billers; we then retain complete outcome pairs at each horizon in $\mathcal{S}_h$. Approval may itself affect month-zero billing, so we interpret these estimates for the selected established-biller sample.

Two-sample 2SLS implementation. We estimate a common first-stage slope on the broad sample, allowing each billing group and invoice-event cohort to have its own intercept:

$$A_j = \eta_{g(j),c(j)} + \pi_B Z_j + v_j, \quad j \in \mathcal{B}, \quad (16)$$

where $g(j)$ distinguishes established billers from the remaining applicants. Applying these coefficients to an outcome sample gives predicted approval

$$\hat{A}_j = \hat{\eta}_{g(j),c(j)} + \hat{\pi}_B Z_j.$$

Regressing $\Delta_h Y_j$ on $\hat{A}_j$ and the outcome controls gives the two-sample 2SLS coefficient. For the ceding probability outcomes, the controls include billing-group-by-cohort intercepts. For the remaining outcomes, the sample contains only established billers, and the controls include cohort intercepts. In both cases, the outcome controls absorb the corresponding first-stage cell intercepts.

Computationally, we obtain the same coefficient by estimating the outcome reduced form

$$\Delta_h Y_j = a_h + X_j' \lambda_h + \delta_h Z_j + u_{jh}, \quad j \in \mathcal{S}_h, \quad (17)$$

with these outcome-specific controls and then computing

$$\hat{\beta}_h = \frac{\hat{\delta}_h}{\hat{\pi}_B}.$$

With one excluded instrument and the controls above, this calculation is algebraically equivalent to the prediction-and-regression implementation. The samples overlap; the ceding regressions use the same broad sample in both stages, while the other outcome samples form subsets of the first-stage sample.

Identifying conditions across samples. This implementation requires the broad first-stage slope to apply to each outcome sample. It also requires officer leniency to be unrelated to unobserved outcome changes, conditional on the specified invoice-event cohorts. Quasi-random assignment within application months alone does not establish that condition. Table 6 reports a sensitivity check using application-month controls.

Local treatment effects. Let $A_j(z)$ denote supplier j 's initial approval under an officer with leniency z . In addition to conditional random assignment and exclusion, we assume monotonicity:

$$A_j(z') \geq A_j(z) \quad \text{for } z' > z.$$

Thus, encountering a more lenient officer never reduces a supplier's initial approval. A positive first-stage coefficient alone does not establish this condition.

For the factoring-use outcomes, A_j indicates approval of at least one initial invoice. Under these assumptions, IV identifies a weighted average effect among suppliers who would receive approval from a more lenient officer but not from a stricter one. For the remaining outcomes, A_j measures approval share. Here, the corresponding interpretation is a weighted average response to additional approval, across the suppliers and approval margins that officer leniency changes. These estimates concern changes in approval rather than changes in actual factoring use.

Our implementation uses the broad first-stage sample to estimate approval responses for narrower outcome samples. The local-effects interpretation therefore additionally requires the broad first-stage slope to apply to each outcome sample and the identifying conditions to hold within that sample. The resulting estimates need not equal average effects for all applicants or for suppliers who never apply.

Application materials. A supplier seeking to sell invoices to Factor X first selects one or more unpaid invoices, authorizes access to its tax and financial records, including its invoice

history, and answers several questions. These materials form its application.

Instrument construction. We use approval and rejection records from the first 14 hours after each supplier’s first application and require at least 30 decisions on other suppliers in the relevant officer-month group. We group these decisions by decision month, which can differ from first-application month $m(j)$. We base the instrument on the initial officer even if another officer handles the application later.

Inference. We use joint heteroskedasticity-robust HC0 covariance, conditional on the estimated leniency score. We account for uncertainty in both the outcome reduced form and the common first stage, retain their covariance when samples overlap, and apply the delta method to their ratio. Outcome whiskers show pointwise 95 percent normal Wald intervals. Table 2 also reports Fieller confidence sets, which allow for denominator uncertainty without linearizing the ratio. Linear IV estimates and their intervals can extend beyond the feasible range of an individual probability change.

For the score-adjusted sensitivity check, we differentiate both slopes with respect to supplier weights, including suppliers who contribute to other suppliers’ leniency scores. This adds uncertainty from estimating leniency while preserving covariance between stages. Table 3 reports the resulting intervals. The officer-clustered sensitivity uses 11 initial officers among target suppliers, with additional score donors contributing to adjusted inference.

For approval share, the first-stage slope is 0.1999. The main standard error is 0.0421, giving $F = 22.58$; accounting for score estimation raises the standard error to 0.0566 and gives $F = 12.46$. For billing at months two and three, the main p -values are 0.018 and 0.043; the score-adjusted values are 0.069 and 0.107. Neither procedure rejects the joint null of zero pre-reference coefficients at the 5 percent level for any of the 19 outcomes. The smallest p -values are 0.125 and 0.304, respectively. These tests and first-stage statistics do not establish the identifying assumptions.

Reporting scale. We calibrate the approval-share contrast using the residual standard deviation of leniency after removing billing-group by invoice-event-cohort means in the 25,468-supplier first-stage sample. Using the unrounded standard deviation (0.0701873) and first-stage slope (0.1998814), we obtain $s = 0.014029140173368574$. We use this contrast in every calculation and round its label to 1.4 percentage points. We treat s as fixed when scaling standard errors and confidence sets. For log outcomes, the plotted quantity is $100s\hat{\beta}_h$, where the dependent variable is $\log(1 + x)$ and we measure monetary values in thousands of USD before taking logs. These effects do not identify percentage changes in mean levels,

particularly when outcomes can equal zero.

Calendar controls. The instrument’s decision-month cells define the officer score; the regression’s invoice-event cohorts control common outcome changes. The invoice-event month precedes the application month for 6,860 suppliers, equals it for 18,595, and follows it for 13. Replacing invoice-event cohorts with application-month controls in the first stage reduces the approval-share F -statistic to 4.36, or 1.97 after accounting for score estimation (Table 6).

B Model details

B.1 Verification of the cost assumptions

We state the formal assumptions for Theorem 1. We collect buyer i ’s roster, valuations, and cost distributions in the competitive environment

$$\mathcal{E}_i = (J_i, (\delta_{ik})_{k \in J_i}, \{F_{ik}\}_{k \in J_i}). \quad (18)$$

Assumption 1 (A1): Independent private costs. Each buyer’s roster J_i contains a positive, finite number of suppliers: $1 \leq |J_i| < \infty$. Conditional on $\mathcal{E}_i$, costs vary independently across suppliers and orders, and each supplier observes only its own realization.

Assumption 2 (A2): Cost distributions.

- (i) Each cost distribution F_{ij} has lower support endpoint $\underline{c}_{ij}$, with $0 \leq \underline{c}_{ij} < \delta_{ij} < \infty$.
- (ii) Each F_{ij} has a continuous, strictly positive density on $(\underline{c}_{ij}, \delta_{ij})$. It assigns zero probability to either endpoint and positive probability to costs above δ_{ij} .
- (iii) For each buyer with at least two suppliers, at least two suppliers satisfy the following lower bound on the probability of costs just below δ_{ij} :

$$F_{ij}(\delta_{ij}) - F_{ij}(\delta_{ij} - v) \geq m_{ij}v \quad \text{for } 0 < v < \varepsilon_{ij}, \quad (19)$$

for some $m_{ij}, \varepsilon_{ij} > 0$.

We fix a financing regime and suppress conditioning on $\mathcal{E}_i$ throughout the appendix unless the comparison requires it. Section 4.1 states the buyer’s allocation and tie rules. The support conditions allow unbounded costs and a density that vanishes or diverges at the lower endpoint. A2(iii) requires enough cost mass immediately below the participation cutoff.

A positive continuous density at that cutoff suffices; the conditions do not require a particular parametric family or a common distribution across suppliers.

The zero outside payoff limits which offers the buyer will accept. Since suppliers submit nonnegative bids, buyer i never purchases from supplier j when $\delta_{ij} < 0$: every feasible price gives $\delta_{ij} - b < 0$. More generally, a supplier must quote a price no greater than δ_{ij} to make a sale. At $\delta_{ij} = 0$, only a zero bid can meet the outside payoff, and the buyer applies the tie rule in Section 4.1. A2(i) restricts the equilibrium analysis to suppliers with $\delta_{ij} > \underline{c}_{ij} \geq 0$, so the nonpositive-taste cases lie outside Theorem 1.

For Weibull costs with positive scale λ_{ij} , shape κ , and taste δ_{ij} , the density at the cutoff equals

$$f_{ij}(\delta_{ij}) = \kappa \delta_{ij}^{\kappa-1} \lambda_{ij}^{-\kappa} \exp[-(\delta_{ij}/\lambda_{ij})^\kappa] > 0.$$

These distributions have lower endpoint zero, no atoms, a continuous positive density at every positive cost, and inactive probability $1 - F_{ij}(\delta_{ij}) = \exp[-(\delta_{ij}/\lambda_{ij})^\kappa] > 0$. Thus every positive Weibull parameter vector satisfies A2, including A2(iii). Fixed financing rates rescale material production costs without changing the Weibull shape. With independent private draws as in A1, the result therefore covers any positive shape and pair-specific scales and tastes, for any finite roster. The proof below derives equilibrium existence, uniqueness, and regularity from the general assumptions.

B.2 Equilibrium and bidding

Theorem 1 (Equilibrium and bidding). *Under A1–A2 (Appendix B.1), each buyer’s auction with at least two suppliers has a unique Bayes–Nash equilibrium, up to types of probability zero and equivalent rejected bids or abstention. Each supplier j uses a continuous, strictly increasing bidding function σ_{ij} on its active cost interval. It abstains almost surely when its cost exceeds δ_{ij} . Let $P_{ij}(c) = W_{ij}(\sigma_{ij}(c))$ denote its probability of winning at the equilibrium bid for cost c . For $\underline{c}_{ij} < c < \delta_{ij}$, $P_{ij}(c) > 0$ and the supplier bids according to (6). Active bids satisfy $c < \sigma_{ij}(c) < \delta_{ij}$. As c approaches δ_{ij} from below, $\sigma_{ij}(c)$ approaches δ_{ij} and $P_{ij}(c)$ approaches the probability that all rivals abstain.*

We fix buyer i and its environment and suppress the buyer index. We first treat a roster with $n \geq 2$ suppliers. We allow each supplier to randomize privately and independently; the argument will show that every equilibrium has an essentially pure representative. We compare Bayes–Nash strategy profiles up to probability-zero types and equivalent choices among rejected prices and abstention.

Maskin and Riley (2003, Proposition 2, p. 407) prove uniqueness under assumptions that include equal upper value endpoints and positive endpoint densities. Our cost assumptions

allow unequal endpoints and densities that vanish at the lowest cost. The comparison below supplies the required extension; the no-gap argument follows their Lemma 11 (pp. 405–407). We use [Reny and Zamir \(2004\)](#) for existence after transforming the inactive tail.

B.2.1 Transformation and participation

Throughout the proof, we divide supplier j 's expected monetary profit by $1 - r_{ij} > 0$. This factor does not depend on the quote, so the normalization leaves optimal strategies unchanged. Write

$$v_j = \delta_j - c_j, \quad z_j = \delta_j - b_j, \quad h_j = \delta_j - \underline{c}_j > 0.$$

An acceptable action satisfies $z_j \in [0, \delta_j]$ and yields normalized expected profit $(v_j - z_j)\Omega_j(z_j)$, where $\Omega_j(z) = W_j(\delta_j - z)$ denotes its winning probability in score units. A rejected price and abstention both correspond to **OUT**. A negative score is *not* an accepted bid in the transformed auction.

Define the unnormalized value CDF on the active range by

$$F_j^V(v) = \mathbb{P}(\delta_j - c_j \leq v) = 1 - F_j(\delta_j - v), \quad 0 \leq v \leq h_j, \quad \alpha_j = F_j^V(0) > 0. \quad (20)$$

A2(i)–(ii) imply $F_j^V(0) = \alpha_j \in (0, 1)$, $F_j^V(h_j) = 1$, continuity on $[0, h_j]$, and a continuous positive density on $(0, h_j)$. They do not impose a positive density limit at either endpoint. We retain α_j throughout; conditioning on participation would change the game.

Lemma B.1 (Participation in every equilibrium). *In any Bayes–Nash equilibrium, allowing independent private randomization, negative-value types abstain almost surely, positive-value types participate and choose $0 \leq z_j < v_j$ almost surely, and*

$$\mathbb{P}(j \text{ abstains}) = \alpha_j, \quad s_0 = \prod_j \alpha_j.$$

Every acceptable deviation by supplier j wins with probability at least $\alpha_{-j} := \prod_{k \neq j} \alpha_k > 0$.

Proof. A negative-value type cannot optimally win with positive probability because every acceptable score gives a negative margin. On the event that all values are negative, which has positive probability, no supplier can win in equilibrium. Independence of costs and private randomizations therefore implies $\prod_j \pi_j^{\text{out}} > 0$, where π_j^{out} denotes supplier j 's probability of abstaining. Each acceptable bid wins whenever all rivals abstain, with probability at least $\prod_{k \neq j} \pi_k^{\text{out}} > 0$. Hence every negative-value type must abstain. Every positive-value type can earn positive profit by choosing $z_j = v_j/2$, which respects $v_j \leq h_j \leq \delta_j$. It therefore

participates with a positive margin. The absence of an atom at zero gives $\pi_j^{\text{out}} = \alpha_j$ and proves the remaining claims. $\square$

The lemma also shows that the score cap creates no hidden restriction: a positive type never chooses a score at or above its value, and $v_j \leq \delta_j$. We can first allow all nonnegative scores and then recover exactly the original feasible equilibrium actions. We cannot instead replace inactive types by strategic zero-valued bidders who submit score zero: that replacement changes an active supplier's payoff from a zero-score deviation through the tie rule.

B.2.2 Existence

Lemma B.2 (Existence). *For every finite $n \geq 2$, the game under A1 and A2(i)–(ii) admits a pure-strategy Bayes–Nash equilibrium with nondecreasing scores in value. It preserves the original inactive probabilities and the manuscript's exact tie rule. The theorem does not require common upper value endpoints or bounded inactive cost tails.*

Proof. Let S_j be independent uniform signals on $[0, 1]$. Replace only the inactive tail by the bounded, strictly increasing value function

$$q_j(u) = \begin{cases} u/\alpha_j - 1, & 0 \leq u \leq \alpha_j, \\ (F_j^V)^{-1}(u), & \alpha_j \leq u \leq 1. \end{cases} \quad (21)$$

The two pieces agree at zero. Continuity and strict increase of F_j^V make q_j continuous and strictly increasing, with range $[-1, h_j]$. This auxiliary game retains exactly the active value distribution and the probability of a negative value.

Apply [Reny and Zamir \(2004, Theorem 2.1, p. 1109\)](#) to the auxiliary first-price auction with reserve zero, losing action $\ell = -2$, uniform ties, and winning payoff $u_j(z, s) = q_j(s_j) - z$. Their assumptions (A1)–(A2), which differ from our A1–A2, appear on pp. 1108–1109; their Appendix proves the theorem on pp. 1121–1125. Here the signal density equals one and satisfies affiliation. At score z the payoff ranges from $-1 - z$ to $h_j - z$. It is continuous in bids, strictly increasing in the bidder's signal, constant in rivals' signals, and negative for sufficiently large bids. The payoff difference between two bids is constant in signals, so their required weak increasing-differences condition holds. Their rule accepts a lone reserve bid, exactly as our game does. Their theorem supplies a pure monotone equilibrium through global deviation inequalities, not merely first-order conditions.

Lemma [B.1](#) forces every auxiliary negative type to choose OUT and every positive type to choose a score below its value. Replace the auxiliary negative values by the original negative values, however long or irregular their tail. Their best response remains OUT; the active

types face identical rival action distributions. The resulting profile is a global equilibrium of the original game. All its serious scores satisfy $z_j < v_j \leq \delta_j$, so the original price constraint also holds. $\square$

For $n = 1$, the supplier chooses price δ_1 whenever $c_1 < \delta_1$ and abstains whenever $c_1 > \delta_1$. This equilibrium is unique up to null types and rejected bids, but the active price function is constant. Any theorem claiming strict active monotonicity must therefore state $n \geq 2$.

B.2.3 Equilibrium distributions and local regularity

Let $\beta_j(v)$ denote an active equilibrium score. The corresponding price satisfies $\sigma_j(c) = \delta_j - \beta_j(\delta_j - c)$. For each supplier, write

$$\Gamma_j(z) = \mathbb{P}(\text{OUT or a score at most } z), \quad p_j(z) = \log \Gamma_j(z), \quad \phi_j(z) = (F_j^V)^{-1}(\Gamma_j(z)).$$

We use the right limit at zero, so $\Gamma_j(0)$ includes any active zero-score pool as well as α_j . Let B_j denote supplier j 's highest equilibrium score and $B = \max_j B_j$. For $z \geq B_j$, set $\Gamma_j(z) = 1$ and $\phi_j(z) = h_j$.

Lemma B.3 (Sorting, atoms, and Lipschitz log CDFs). *Every equilibrium has an essentially pure nondecreasing score strategy. Each Γ_j is continuous on $(0, \infty)$; at most one supplier has an active atom at zero. The aggregate score support is $[0, B]$, and at least two suppliers have each interior score in their closed supports. Each p_j is locally Lipschitz on $(0, \infty)$. Each ϕ_j is locally absolutely continuous, including across its upper-support cap.*

Proof. Consider two positive values $v < v'$ and optimal scores z, z' . The two global best-response inequalities imply

$$(v' - v)[\Omega_j(z') - \Omega_j(z)] \geq 0.$$

If $z > z'$, monotonicity of Ω_j forces equality of the winning probabilities, in which case the lower score strictly improves the margin. Thus all optimal score sets respect the order of values. A type with two distinct optimal scores occupies a nonempty interval between them that no other type can occupy; assigning a rational number to each such interval shows that at most countably many types can mix nontrivially. The continuous active value law therefore gives an essentially pure representative.

An optimal positive type earns at least $v\alpha_{-j}$ by choosing zero, and its winning probability never exceeds one. Hence every equilibrium score satisfies

$$v - z \geq v\alpha_{-j}, \quad B_j \leq (1 - \alpha_{-j})h_j < h_j. \tag{22}$$

Two suppliers cannot have atoms at a common nonnegative score: whenever the other suppliers abstain, a sufficiently small increase breaks the tie at a strictly positive margin.

Suppose only supplier j has an atom at a positive score z . A rival who chooses a score immediately below z has a margin bounded away from zero by (22). Increasing its score slightly above z raises its winning probability by at least the atom's mass times the probability that all remaining suppliers abstain. The gain stays positive as the bid increase tends to zero. A common sufficiently small left neighborhood of z therefore contains no rival bids. Supplier j can lower its atom into that neighborhood without changing its winning probability, a contradiction. This also explains why the argument does not exclude a lone atom at the reserve zero.

The aggregate support starts at zero because arbitrarily small positive values participate and bid below their values. If the aggregate support had a gap (s, t) , a supplier with scores approaching t from above would, in the limit, choose t optimally at a positive margin. Atomlessness makes the winning probability at s and t the same, so the supplier would prefer s . Thus the aggregate support has no gap. If only one supplier had a given interior point in its closed support, all rivals would have constant CDFs in a neighborhood. That supplier could shade any interior score there. Hence every interior point belongs to at least two suppliers' closed supports.

Fix a compact positive-score interval. At any point z of the aggregate support, choose two suppliers whose closed supports contain z . Taking limits of optimizing types shows that z optimizes for the corresponding values $\phi_j(z)$. Their margins have a uniform positive lower bound on the compact interval by (22). For sufficiently small $t - z > 0$, global optimality gives

$$\sum_{k \neq j} [p_k(t) - p_k(z)] \leq \log \frac{\phi_j(z) - z}{\phi_j(z) - t} \leq C(t - z).$$

Apply the inequality to both suppliers and add. Nonnegative CDF increments then bound the increment of $\sum_k p_k$ by $2C(t - z)$. Outside the aggregate support all increments vanish. Subdivision yields local Lipschitz continuity of the aggregate and of each p_j .

The function $(F_j^V)^{-1}$ has a continuous positive derivative on compact interior quantile intervals. Its derivative integrates to its finite total range, so it remains absolutely continuous up to the endpoints even if that derivative diverges there. Composing it with the monotone Lipschitz function Γ_j preserves absolute continuity. Thus ϕ_j has the stated local regularity. This argument does not require a positive density at the highest value. $\square$

B.2.4 A global comparison of two equilibria

We now prove joint uniqueness without first ruling out gaps or reserve pooling. Let $U_j(v)$ denote supplier j 's optimized profit in score units. For $z > 0$,

$$\Omega_j(z) = \exp \left(\sum_{k \neq j} p_k(z) \right).$$

At zero we use its right limit when defining the expressions below. A supplier can approach that payoff with positive scores, so the supremum defining U_j respects the corresponding global deviation inequality even if another supplier has a zero-score atom.

Choose T_j strictly between B_j and h_j . For $0 < z \leq T_j$, define the nonnegative log deviation loss

$$L_j(z) = \log U_j(\phi_j(z)) - \log[\phi_j(z) - z] - \sum_{k \neq j} p_k(z) \geq 0. \quad (23)$$

This expression has a positive margin. On a gap in supplier j 's score range, both gap endpoints optimize for the same limiting type; even the larger endpoint lies below that type's value. Above B_j , the choice $T_j < h_j$ gives the required positive margin directly. At every point of j 's score support, global optimality gives $L_j = 0$.

Let $S = \sum_k p'_k$ and $A_j(z) = 1/[\phi_j(z) - z]$. The envelope for the convex optimized value, the chain rule for absolutely continuous functions, and Lemma B.3 imply, almost everywhere,

$$L'_j = A_j - S + p'_j, \quad L_j p'_j = 0. \quad (24)$$

To check the cancellation in the first identity, at points where $\phi'_j > 0$, the score lies in j 's support and

$$U_j(\phi_j) = (\phi_j - z)\Omega_j(z), \quad U'_j(\phi_j) = \Omega_j(z).$$

The derivatives involving ϕ'_j therefore cancel. At points where $\phi'_j = 0$, they vanish. The second identity follows because L_j vanishes on the support of dp_j . We have used global optimality to obtain these identities; solving them in isolation would not prove equilibrium.

We also need the lower boundary

$$\lim_{z \downarrow 0} L_j(z) = 0. \quad (25)$$

If j pools at zero, its limiting type is positive, all rivals lack zero atoms, and optimality at zero proves the limit. Otherwise $\phi_j(z) \downarrow 0$. Write $w_j^0 = \lim_{z \downarrow 0} \Omega_j(z) > 0$. Deviations with positive scores tending to zero give $U_j(v) \geq v w_j^0$. For an optimizing type with small positive value, $z \leq v$ and $\Omega_j(z) \rightarrow w_j^0$, so $z/v \rightarrow 0$ and $U_j(v)/v \rightarrow w_j^0$. The same bounds extend

across gaps by taking the next optimizing type. Hence $z/\phi_j(z) \rightarrow 0$, and (23) converges to zero. This step accounts explicitly for the true score-zero tie rule.

Compare two equilibria, superscripted A and D . For each supplier choose a common T_j above both of its score endpoints and below h_j , possible by (22). Write

$$d_j = p_j^A - p_j^D, \quad d = \sum_j d_j, \quad \Delta L_j = L_j^A - L_j^D, \quad \Delta A_j = A_j^A - A_j^D.$$

The first identity in (24) gives

$$\Delta A_j = d' - d'_j + \Delta L'_j.$$

Multiply by d_j , integrate supplier j 's equation on $[\varepsilon, T_j]$, and sum. Each d_j and d'_j vanishes above T_j , so we can extend only the cross terms $d_j d'_k$ to the common endpoint $\max_j T_j$. No reciprocal needs evaluation beyond its supplier's value endpoint. Integration by parts and (24) give

$$\begin{aligned} & \frac{1}{2} \left[d(\varepsilon)^2 - \sum_j d_j(\varepsilon)^2 \right] + \sum_j d_j(\varepsilon) \Delta L_j(\varepsilon) \\ &= \sum_j \int_\varepsilon^{T_j} \left[-d_j \Delta A_j + L_j^A(p_j^D)' + L_j^D(p_j^A)' \right] dz. \end{aligned} \quad (26)$$

The upper boundary terms vanish because $d_j(T_j) = 0$. At the lower endpoint, (25) makes the loss boundary term vanish as $\varepsilon \downarrow 0$. Each equilibrium has at most one zero-score pool, so

$$p_j^E(0+) = \log \alpha_j + \eta_j^E, \quad \eta_j^E \geq 0, \quad \#\{j : \eta_j^E > 0\} \leq 1 \quad (E = A, D).$$

Consequently $d(0+)^2 - \sum_j d_j(0+)^2 \leq 0$: the only possible cross product comes from different pooling suppliers and has opposite signs. The left side of (26) therefore has a nonpositive limit. Strict increase of $(F_j^V)^{-1}$ implies

$$d_j \Delta A_j \leq 0,$$

with strict inequality wherever $d_j \neq 0$, because $1/(\phi - z)$ strictly decreases in ϕ . Every integrand on the right side of (26) is therefore nonnegative. If the profiles differ at any positive score, continuity gives a compact interval on which the first term has a strictly positive integral. That fixed positive contribution survives as $\varepsilon \downarrow 0$, contradicting the nonpositive limit on the left. This argument requires no assumed integrability at zero. Hence all score CDFs agree. The monotone quantile representation then gives identical strategies almost everywhere. Lemma B.1 identifies all inactive actions modulo rejection. This proves joint

uniqueness even before imposing (19).

B.2.5 Excluding reserve pooling

Suppose supplier j has a positive active pool at zero and choose a positive optimizing value v_* in that pool. No rival has a zero-score atom. For small $z > 0$, its global best-response inequality gives

$$(v_* - z) \prod_{k \neq j} \Gamma_k(z) \leq v_* \prod_{k \neq j} \alpha_k.$$

Since each factor exceeds or equals its positive inactive mass, $\Gamma_k(z) - \alpha_k = O(z)$ for every rival k . If at least two suppliers satisfy (19), some such supplier k differs from j .

Supplier k cannot optimally choose zero at a positive value because a small positive score breaks supplier j 's atom. The lower-boundary argument above gives $\beta_k(v)/v \rightarrow 0$ as $v \downarrow 0$. At $z = \beta_k(v)$, monotonicity gives

$$\Gamma_k(z) - \alpha_k \geq F_k^V(v) - \alpha_k \geq m_k v,$$

while the preceding $O(z)$ bound gives $\Gamma_k(z) - \alpha_k = O(\beta_k(v)) = o(v)$, a contradiction. Thus no active zero atom exists. Atomlessness and sorting now make active score strategies strictly increasing. The continuity proof follows next.

B.2.6 Ruling out gaps in individual score ranges

We give the risk-neutral version of the Maskin–Riley no-gap argument and justify the finite-interval step explicitly. The argument uses only local incentive inequalities on an open positive-score interval: at every point in supplier k 's score support, its inverse type ϕ_k optimizes $(v - z) \exp(\sum_{j \neq k} p_j(z))$ against every alternative score in that interval. Each support type has a positive margin. Constant rival log CDFs only multiply this objective by a positive constant. These properties, continuity, and local absolute continuity therefore survive when we remove any log CDF that stays constant on the interval. We use this observation for induction; we do not presume that the restricted functions constitute an equilibrium of a newly normalized auction.

We prove by induction on the number of potentially varying log CDFs that each one's support has no interior gap. With one varying function, its supplier faces constant rival winning probability and cannot optimally use any interior interval of scores. With two, every interior point of the aggregate support must belong to both suppliers' supports: otherwise one supplier could shade where only its own CDF changes. The same shading argument rules out gaps in the aggregate support using only the local incentive inequalities.

For the induction step, suppose supplier j has a gap (s, t) whose endpoints lie in its support. Its inverse type stays constant there, say $\phi_j(z) = w$. Both endpoints optimize for w , and $w > t$. Remove the constant p_j on this gap. The induction hypothesis implies that each remaining supplier's support intersects (s, t) in an interval, possibly empty. Their finitely many entry and exit endpoints partition (s, t) into finitely many intervals with a fixed set A of varying suppliers. At least two suppliers vary on each such interval, since the aggregate has no gap and a lone varying supplier could shade.

Write $m = |A| \geq 2$, $A_k(z) = 1/[\phi_k(z) - z]$ for $k \in A$, and $S = \sum_{k \in A} p'_k$. At almost every point of a fixed-set interval, local optimality implies

$$S - p'_k = A_k, \quad S = \frac{\sum_{k \in A} A_k}{m-1}, \quad p'_k = S - A_k \geq 0. \quad (27)$$

The right sides are continuous, so these identities upgrade the local absolute continuity to continuous differentiability. Positive interior value density gives continuous differentiability of each ϕ_k on the interval as well. We have $\phi'_k \geq 0$, and hence

$$A'_k = (1 - \phi'_k)A_k^2 \leq A_k^2, \quad S' \leq \frac{\sum_{k \in A} A_k^2}{m-1} < S^2.$$

The strict inequality follows from $A_k \leq S$, $\sum_k A_k = (m-1)S$, and $\sum_k p'_k = S > 0$, which makes at least one $A_k < S$.

We must also check the partition endpoints. Let S_- and S_+ denote the two one-sided limits. If supplier k exits, its left first-order condition gives $S_- - (p'_k)_- = A_k$. Optimality of its last score implies the right derivative of its log payoff is nonpositive, so $S_+ \leq A_k \leq S_-$. If suppliers only enter, let m_- denote the number of incumbent varying suppliers. Sum (27) on both sides and use $A_k = S_+ - (p'_k)_+ \leq S_+$ for the entrants. This gives

$$(m_- - 1)S_+ \leq (m_- - 1)S_-,$$

so again $S_+ \leq S_-$. Any simultaneous exit already gives the first inequality. Thus S has no upward jump at a partition endpoint.

Set $K(z) = \exp[-\sum_k p_k(z)]$. On each fixed-set interval,

$$K'' = K(S^2 - S') > 0,$$

and at a partition endpoint $K' = -SK$ can jump only upward. Hence K is convex across the gap, with strict curvature on every open piece. Supplier j 's CDF stays constant there, say $\Gamma_j = g_j$. Let $U_* > 0$ denote the common optimal payoff of type w at the two gap endpoints.

Global optimality gives

$$(w - z)\Omega_j(z) \leq U_*, \quad K(z) = \frac{1}{g_j\Omega_j(z)} \geq \frac{w - z}{g_jU_*}.$$

Equality holds at both endpoints. The expression on the right is the chord joining the two endpoint values of K . Convexity puts K below that chord; global optimality puts it above. Equality throughout would contradict strict curvature. This completes the induction and rules out every gap with positive endpoints.

Under (19), no supplier has a zero atom, and arbitrarily small positive values choose arbitrarily small positive scores. Thus no supplier can have an initial gap $(0, t)$ either. Each active score range is consequently $(0, B_j)$ with its endpoint limits. An atomless monotone strategy with no range gaps has a continuous, strictly increasing representative. Transforming back to costs proves the strategy regularity in Theorem 1.

A2(iii) supplies a sufficient local restriction for strict active bidding. It imposes no density restriction at the lowest cost, no log-concavity condition, and no uniform lower bound across parameter vectors.

B.2.7 The coupled boundary problem and global verification

For completeness, we describe the inverse equations under the no-pooling condition and verify all deviations. This step also distinguishes a valid equilibrium boundary problem from a collection of first-order conditions.

Each supplier has a score range $(0, B_j)$, with possibly different upper endpoints. Between successive endpoints, equations (27) hold for the suppliers whose CDFs still increase. At an internal exit, let L denote the leaving suppliers and let $m_+ \geq 2$ suppliers continue. Optimality of a leaving supplier's last score gives $S_+ \leq A_j \leq S_-$. The equations on the two sides also imply

$$(m_+ - 1)(S_+ - S_-) = \sum_{j \in L} (S_- - A_j) \geq 0.$$

Thus $S_+ = S_-$ and $A_j = S_- = S_+$ for every leaver. In particular, each leaving p'_j approaches zero. Continuing derivatives remain continuous. This argument never evaluates $(F_j^V)'(h_j)$.

An active derivative p'_j cannot vanish at an interior point of a fixed-set interval. Otherwise $A_j = S$ and $\phi'_j = 0$ there, so $(p'_j)' = S' - S^2 < 0$, contradicting nonnegativity of p'_j immediately to the right. The same right-side argument covers an internal exit by another supplier. Hence $p'_j > 0$ throughout $(0, B_j)$, and the positive interior primitive density gives $\phi'_j > 0$. The active direct strategy is therefore C^1 with a positive derivative in value, and the corresponding price strategy is C^1 with a positive derivative in cost.

For a supplier that has exhausted its support, put

$$D_j(z) = S(z) - \frac{1}{h_j - z}, \quad B_j < z < h_j.$$

At an internal exit $D_j(B_j+) = 0$. On each subsequent fixed-set interval,

$$D'_j \leq \left(S + \frac{1}{h_j - z} \right) D_j.$$

An integrating factor preserves $D_j \leq 0$. Internal transitions leave S continuous, and the final transition drops S to zero, so they cannot overturn that inequality. If B_j equals the overall highest score, it holds directly because all rival CDFs stay constant above that score. We obtain the terminal condition

$$\sum_{k \neq j} p'_k(z) \leq \frac{1}{h_j - z}, \quad B_j < z < h_j. \quad (28)$$

The coupled boundary problem has unknown endpoints $0 < B_j < h_j$. It consists of the active equations

$$\sum_{k \neq j} p'_k = \frac{1}{(F_j^V)^{-1}(e^{p_j}) - z} \quad (0 < z < B_j),$$

the conditions $p_j(0) = \log \alpha_j$, $p_j(B_j) = 0$, $p'_j = 0$ above B_j , positive active inverse margins and derivatives, and (28). We require continuity and piecewise C^1 regularity, with the finitely many upper score endpoints as the possible breakpoints. The equilibrium that we constructed proves existence of a solution with these properties.

Conversely, take any such solution and define β_j by inverting $\phi_j = (F_j^V)^{-1}(e^{p_j})$ on $(0, h_j)$. For a positive type v and a positive score $z < v$ inside its own score range,

$$\frac{d}{dz} \log[(v - z)\Omega_j(z)] = \frac{1}{\phi_j(z) - z} - \frac{1}{v - z}.$$

This derivative is positive below $\beta_j(v)$ and negative above it. Beyond B_j , (28) bounds it above by

$$\frac{1}{h_j - z} - \frac{1}{v - z} < 0 \quad (v < h_j).$$

Scores at or above v give nonpositive profit. At zero, atomlessness makes the actual winning probability equal its positive-score limit, so the same comparison covers the zero deviation. Abstention gives zero, while the prescribed active bid gives positive profit. Negative types choose OUT. Thus every solution of the full boundary problem generates global best responses

against every feasible deviation. Joint equilibrium uniqueness then proves uniqueness of this coupled solution as well. First-order conditions without the boundaries and terminal conditions would not support this conclusion.

B.2.8 Bidding formula and cutoff limits

Completion of the proof of Theorem 1. The preceding steps establish existence, joint uniqueness, and continuous, strictly increasing active strategies. We now derive the bidding formula and its boundary conditions.

We next extend optimality from almost every type to every interior active type. Positive cost density makes the optimizing types dense in $(\underline{c}_j, \delta_j)$. Continuity first extends the weak bounds $c \leq \sigma_j(c) \leq \delta_j$ to that interval, and strict increase implies $\sigma_j(c) < \delta_j$ there. Strict increase and atomless active costs rule out atoms in acceptable bids, so W_j is continuous on the acceptable bid interval. We can now take limits of the best-response inequality for each fixed deviation along optimizing types. This extends global optimality to every interior active type. The profitable midpoint deviation then gives

$$c < \sigma_j(c) < \delta_j, \quad P_j(c) \geq \alpha_{-j} > 0, \quad \underline{c}_j < c < \delta_j. \quad (29)$$

We include the option to abstain and define optimized normalized expected profit by

$$V_j(c) = \max \left\{ 0, \sup_{0 \leq b \leq \delta_j} (b - c)W_j(b) \right\}. \quad (30)$$

Every acceptable bid satisfies $b - c \leq 0$ when $c \geq \delta_j$. Abstention attains zero, so

$$V_j(c) = 0 \quad \text{for } c \geq \delta_j, \quad V_j(\delta_j) = 0. \quad (31)$$

This boundary follows from the buyer's acceptance rule. We retain the full cost law, including the mass $1 - F_j(\delta_j)$ above the cutoff.

For two active costs $c < c'$, each type can submit the other type's equilibrium bid. Their global best-response inequalities imply

$$(c' - c)P_j(c') \leq V_j(c) - V_j(c') \leq (c' - c)P_j(c). \quad (32)$$

Each feasible action gives an affine payoff in cost with slope in $[-1, 0]$. Their supremum V_j is therefore convex and 1-Lipschitz, hence absolutely continuous. The bounds in (32) give

$V'_j(c) = -P_j(c)$ almost everywhere. Integrating to the cutoff and using (31), we obtain

$$V_j(c) = \int_c^{\delta_j} P_j(u) du, \quad \underline{c}_j < c < \delta_j. \quad (33)$$

At an equilibrium bid, $V_j(c) = [\sigma_j(c) - c]P_j(c)$. Dividing (33) by the positive winning probability and restoring the buyer index gives (6).

Finally, the bounds in (29) imply $\lim_{c \uparrow \delta_j} \sigma_j(c) = \delta_j$. As the bid approaches this cap, supplier j wins only when all rivals abstain, in the limit. Hence

$$\lim_{c \uparrow \delta_j} P_j(c) = \prod_{k \neq j} [1 - F_k(\delta_k)] > 0. \quad (34)$$

The markup nevertheless converges to zero. A type with cost exactly δ_j can bid δ_j or abstain and earn zero either way; A2 assigns probability zero to this case. $\square$

B.3 Winning probabilities, shares, and transaction prices

We derive supplier shares and transaction-price distributions from the bidding functions in Section 4.2. For a roster with at least two suppliers, let $\underline{b}_{ik}$ denote supplier k 's lowest active bid, $\underline{b}_{ik} = \lim_{c \downarrow \underline{c}_{ik}} \sigma_{ik}(c)$. Strict monotonicity gives an inverse bidding function on the interior of the active bid range. For a bid level t in that range, $\sigma_{ik}^{-1}(t)$ returns the cost at which supplier k quotes t . We use the same notation outside the active range and define

$$\sigma_{ik}^{-1}(t) = \begin{cases} \underline{c}_{ik}, & t \leq \underline{b}_{ik}, \\ \text{the unique } c \text{ with } \sigma_{ik}(c) = t, & \underline{b}_{ik} < t < \delta_{ik}, \\ \delta_{ik}, & t \geq \delta_{ik}. \end{cases} \quad (35)$$

When buyer i has only one supplier k , that supplier quotes δ_{ik} whenever its cost falls below that value and otherwise abstains. We set $\sigma_{ik}^{-1}(t) = \underline{c}_{ik}$ when $t < \delta_{ik}$ and $\sigma_{ik}^{-1}(t) = \delta_{ik}$ when $t \geq \delta_{ik}$. The upper extension preserves the probability that supplier k abstains. For every finite bid level b , supplier j 's submitted bid, including $+\infty$ for abstention, satisfies

$$\Pr(B_{ija} \leq b) = F_{ij}(\sigma_{ij}^{-1}(b)). \quad (36)$$

For a lone supplier, the bid distribution places mass $F_{ij}(\delta_{ij})$ at δ_{ij} and the remaining mass at $+\infty$. We interpret $dF_{ij}(\sigma_{ij}^{-1}(b))$ as the Stieltjes measure of this composite function on finite bids. This measure includes the lone supplier's mass at δ_{ij} without conditioning on participation.

Equation (5) gives the winning probability in terms of rivals' bid distributions. We can also write each rival's threshold in cost units. At supplier j 's equilibrium bid, the corresponding rival-cost cutoff is

$$c_{ik}^*(c) = \sigma_{ik}^{-1}(\delta_{ik} - \delta_{ij} + \sigma_{ij}(c)). \quad (37)$$

When this cutoff lies inside the rival's active cost range, it solves $\delta_{ik} - \sigma_{ik}(c_{ik}^*(c)) = \delta_{ij} - \sigma_{ij}(c)$. Thus an active supplier j wins exactly when every rival's cost exceeds its cutoff, apart from ties, and

$$P_{ij}(c) = \prod_{\substack{k \in J_i \\ k \neq j}} [1 - F_{ik}(c_{ik}^*(c))], \quad \underline{c}_{ij} < c < \delta_{ij}. \quad (38)$$

We set $P_{ij}(c) = 0$ for $c > \delta_{ij}$ because these types abstain. The endpoint values do not affect any integral below. For a lone supplier, the empty product equals one.

Averaging supplier j 's winning probability over its cost draws gives its share of buyer i 's orders, $s_{ij} = \Pr(j^*(a) = j)$:

$$s_{ij} = \int_{\underline{c}_{ij}}^{\delta_{ij}} P_{ij}(c) dF_{ij}(c). \quad (39)$$

All suppliers abstain when their costs exceed their respective participation cutoffs. Independence gives the no-purchase probability

$$s_{i0} = \prod_{j \in J_i} [1 - F_{ij}(\delta_{ij})], \quad s_{i0} + \sum_{j \in J_i} s_{ij} = 1. \quad (40)$$

A1–A2 imply $s_{ij} > 0$ and $0 < s_{i0} < 1$. Conditional on a purchase, supplier j 's share equals

$$\Pr(j^*(a) = j \mid j^*(a) \neq 0) = \frac{s_{ij}}{1 - s_{i0}}, \quad j \in J_i. \quad (41)$$

Let B_{ia}^w denote the price buyer i pays when it purchases. Supplier j 's winning-price distribution equals

$$L_{ij}(p) = \Pr(B_{ia}^w \leq p \mid j^*(a) = j) = \frac{1}{s_{ij}} \int_0^p W_{ij}(b) dF_{ij}(\sigma_{ij}^{-1}(b)), \quad 0 \leq p \leq \delta_{ij}. \quad (42)$$

The integral weights each submitted bid by its probability of winning. Dividing by s_{ij} conditions on supplier j winning. The CDF equals zero for $p < 0$ and one for $p \geq \delta_{ij}$. Equivalently, we can integrate over the supplier's cost draws:

$$L_{ij}(p) = \frac{1}{s_{ij}} \int_{\underline{c}_{ij}}^{\delta_{ij}} \mathbf{1}\{\sigma_{ij}(c) \leq p\} P_{ij}(c) dF_{ij}(c). \quad (43)$$

Supplier j 's first two conditional winning-price moments satisfy

$$\begin{aligned} m_{\ell,ij} &= \mathbb{E}[(B_{ia}^w)^\ell \mid j^*(a) = j], \quad \ell = 1, 2, \\ &= \frac{1}{s_{ij}} \int_0^{\delta_{ij}} b^\ell \prod_{\substack{k \in J_i \\ k \neq j}} [1 - F_{ik}(\sigma_{ik}^{-1}(b + \delta_{ik} - \delta_{ij}))] dF_{ij}(\sigma_{ij}^{-1}(b)). \end{aligned} \quad (44)$$

Using $b = \sigma_{ij}(c)$ and $P_{ij}(c) = W_{ij}(\sigma_{ij}(c))$ gives the equivalent cost-space representation

$$m_{\ell,ij} = \frac{1}{s_{ij}} \int_{\underline{c}_{ij}}^{\delta_{ij}} \sigma_{ij}(c)^\ell P_{ij}(c) dF_{ij}(c), \quad \ell = 1, 2. \quad (45)$$

The bid CDF retains each supplier's inactive mass at $+\infty$; we integrate only over acceptable bids. The first moment gives the mean transaction price, and $m_{2,ij} - m_{1,ij}^2$ gives its variance. These formulas condition on the supplier winning, rather than simply submitting an acceptable bid.

At an interior optimum where W_{ij} is differentiable and $W'_{ij}(b) < 0$, the first-order condition for (4) also gives

$$W_{ij}(b) + (b - c)W'_{ij}(b) = 0, \quad c = b - \frac{W_{ij}(b)}{-W'_{ij}(b)}. \quad (46)$$

This expression links an observed equilibrium bid to cost when the winning-probability function satisfies these local conditions. The global bidding characterization in Theorem 1 does not require this differentiability condition at every bid.

B.4 Cost distributions across financing regimes

We use B to denote bank credit alone and F to denote bank credit with access to factoring. The financing rule in Section 4.1 gives $r_{ij}^B = r_{ij}^{\text{bank}}$ and $r_{ij}^F = \min\{r_{ij}^{\text{bank}}, r_{ij}^{\text{fac}}\}$ for suppliers with access to both options. For suppliers without access to factoring, $r_{ij}^F = r_{ij}^B$. Holding material production-cost distributions fixed, costs and their distributions in each regime $T \in \{B, F\}$ satisfy

$$c_{ija}^T = \frac{c_{ija}^{\text{prod}}}{1 - r_{ij}^T}, \quad F_{ij}^T(c) = F_{ij}^{\text{prod}}((1 - r_{ij}^T)c). \quad (47)$$

Since $r_{ij}^F \leq r_{ij}^B$, the same production-cost draw gives $c_{ija}^F \leq c_{ija}^B$, and $F_{ij}^F(c) \geq F_{ij}^B(c)$ for every $c \geq 0$. A lower financing rate reduces cost for every positive production-cost draw. Under each regime that satisfies A1–A2, we solve the unique equilibrium and evaluate the shares and price moments in Appendix B.3 using that regime's cost distributions and bidding functions.

C Estimation Appendix

C.1 Estimation sample and outside-share construction

We construct our sample from road-freight invoices, treating each invoice as a purchase and its gross amount as the transaction price. The initial sample contains 50 buyers with at least 500 purchases and buyer–supplier relationships with at least ten invoices. We use invoices from January 2019 onward and require financing inputs for every supplier in the buyer’s set. After removing relationships without remaining purchases, we exclude nine single-supplier buyers and 15 additional buyers whose largest supplier accounts for at least 85% of completed purchases. The final sample contains 26 buyers, 255 suppliers, 304 buyer–supplier relationships, and 29,706 purchases, spanning January 2019–March 2026. Table C.1 reports the sample at each step.

Invoices record completed purchases but omit orders that buyers forgo. Our outside-share construction draws inspiration from IO demand applications that specify potential market size and assign the unpurchased share to the outside option (Berry et al., 1995; Nevo, 2001). We adapt this approach by using each buyer’s monthly invoice spending as a measure of purchasing activity. Let Y_{it} denote buyer i ’s total gross invoice spending in month t , and let T_i contain the months with at least one purchase in the sample. We choose the 30th percentile of these monthly totals, B_i , as the reference level of activity and calculate

$$\hat{s}_{i0} = \frac{1}{|T_i|} \sum_{t \in T_i} \max \left\{ 1 - \frac{Y_{it}}{B_i}, 0 \right\}. \quad (48)$$

We give months equal weight and count only shortfalls below the benchmark.³¹ This calibration interprets proportional spending shortfalls as forgone orders; it therefore abstracts from shortfalls that instead reflect lower prices, smaller orders, or seasonal changes in purchasing needs.

We combine the constructed outside share with observed purchase counts to obtain the unconditional winning shares that enter estimation. If n_{ij} counts buyer i ’s purchases from supplier j and $n_i = \sum_{k \in J_i} n_{ik}$, then $\hat{s}_{ij} = (1 - \hat{s}_{i0})n_{ij}/n_i$, so $\hat{s}_{i0} + \sum_{j \in J_i} \hat{s}_{ij} = 1$. We hold $\hat{s}_{i0}$ fixed while estimating preferences and cost parameters, and condition inference on this supplied input. These shares set the baseline frequency of forgone orders. In counterfactuals, purchase probabilities respond to financing costs at fixed preferences and potential orders, generating the output-expansion effect.

³¹We sort the $|T_i|$ monthly totals and select the observation at rank $\lceil 0.30|T_i| \rceil$ to obtain B_i . Months with spending at or above B_i contribute zero shortfall. We omit months without observed purchases rather than assign them zero spending.

Table C.1: Estimation sample construction

Sample restriction	Buyers	Relationships	Purchases
Initial road-freight sample	50	352	67,394
Invoices from January 2019 onward	50	352	67,297
Complete financing inputs and positive wins	50	351	66,883
At least two suppliers per buyer	41	342	54,683
Largest supplier share below 85%	26	304	29,706

Notes: Each row reports the remaining sample after the stated restriction. Financing requirements remove 414 invoices and leave one relationship without purchases. Supplier shares use purchase counts.

C.2 Financing inputs

Chita’s pricing tables describe its factoring list rates as a function of supplier and buyer characteristics and invoice amount. We use this pricing structure to reconstruct missing historical schedules from observed offers, choosing the pricing coefficients to match the most common quoted rates within each category. In a benchmark using the known February 2026 pricing table, we reproduce 99.48% of its entries within 0.01 percentage points.³² We combine interest and commissions, net of VAT, to obtain the all-in financing charge as a fraction of the invoice amount.

We construct loan-rate inputs from a common time component and persistent supplier differences. We use accepted offers that lead to completed factoring transactions as intermittent evidence about suppliers’ alternative financing costs. If suppliers accept factoring only when it costs no more than alternative financing, an accepted rate bounds the alternative rate from below. We therefore use each supplier’s highest accepted monthly factoring rate as a proxy for its loan rate. For each invoice date t , we calculate the median of these proxies across other suppliers in the same month to obtain the common component, $R_{-j,t}$.³³

We measure supplier j ’s distance from this common component when its financing history first supports a comparison with its peers. We preserve that difference, a_j , across dates and buyers, so the common component governs the evolution of its imputed loan rate. Specifically, we construct

$$h(\hat{r}_{jt}^L) = h(R_{-j,t}) + a_j, \quad h(r) = \log\left(\frac{r}{0.20 - r}\right). \quad (49)$$

We calculate a_j from the supplier’s earliest supported differences on this transformed scale and apply it throughout the sample, including earlier dates.³⁴ Suppliers without individual

³²The benchmark covers 2,912 pricing categories. We hold the known additive term and rate caps fixed while recovering the remaining pricing coefficients. This comparison measures recovery of list rates.

³³We use offers that lead to completed factoring transactions and convert their all-in charges into monthly rates. Each supplier’s proxy uses the highest rate among offers with invoice issue dates in the same month and no later than t . We require at least five other suppliers and include suppliers outside road freight.

³⁴At the earliest date with support, we take the median of the available supplier-month differences between

evidence receive $a_j = 0$ and therefore the common rate. We convert the monthly loan rates to the invoice’s financing horizon and combine them with factoring rates to construct the relationship inputs that we hold fixed during structural estimation.³⁵

C.3 Construction of the cost groups

We form five cost groups using preliminary estimates that allow each buyer–supplier relationship to have its own financing-adjusted cost scale, $\hat{\lambda}_{ij}^{\text{pilot}}$, and fix the Weibull shape at $\kappa = 2$. We remove the financing adjustment and take logarithms to obtain $z_{ij} = \log(\bar{\rho}_{ij} \hat{\lambda}_{ij}^{\text{pilot}})$. We then group relationships with similar values of z_{ij} , weighting each relationship by its observed purchase count.³⁶ We hold group membership fixed while jointly estimating the five cost scales, five group-specific shapes, and relationship-specific preferences. A supplier can belong to different groups across buyers because we classify relationships. Each buyer retains its original supplier roster, so grouping does not change which suppliers compete. Table C.2 reports the cost-parameter estimates.

Table C.2: Cost distribution parameters

	λ_1^C	λ_2^C	λ_3^C	λ_4^C	λ_5^C	κ_1	κ_2	κ_3	κ_4	κ_5
Estimate	468	1,372	3,644	7,854	27,542	1.908	1.652	2.230	2.305	1.887

Notes: We report Weibull scales λ_g^C in USD before financing and dimensionless shapes κ_g . We do not report standard errors for these estimates.

C.4 Estimation criterion and computation

We implement the limiting criterion in Section 5.3 by minimizing price-moment discrepancies subject to exact share matching. Let n_{ij} count observed purchases from supplier j by buyer

the transformed proxy and transformed common component. We use monthly source rates strictly between zero and 20%; the inverse transformation keeps imputed monthly rates in the same interval.

³⁵We multiply the monthly loan rate by the inclusive number of days from invoice issue to original contractual due date, divided by 30. Factoring charges use the inclusive issue-to-agreed-maturity horizon. We use the winner’s observed financing method; for a rival, we use its latest earlier invoice with the same buyer, or its earliest later invoice when none precedes the purchase. We carry only the method and apply the current purchase’s rate. Across all eligible opportunities $\mathcal{A}_{ij}$, including losses, we calculate $\bar{\rho}_{ij} = |\mathcal{A}_{ij}|^{-1} \sum_{a \in \mathcal{A}_{ij}} (1 - r_{ija})$. The input in Section 5.1 is $r_{ij} = 1 - \bar{\rho}_{ij}$, giving $\lambda_{ij} = \lambda_{g(i,j)}^C / \bar{\rho}_{ij}$ with unchanged shape κ .

³⁶We sort the scores and choose five contiguous groups to minimize the count-weighted sum of squared deviations from each group’s weighted mean. An exact dynamic program solves this partition problem, keeps tied scores together, and chooses the earliest split when criteria tie.

i , $N = \sum_i \sum_{j \in J_i} n_{ij}$, and $\hat{\pi}_{ij} = n_{ij}/N$. We minimize

$$Q_N(\theta) = \sum_i \sum_{j \in J_i} \hat{\pi}_{ij} \sum_{r=1}^2 \left[\frac{m_{r,ij}^M(\theta) - \hat{m}_{r,ij}}{\hat{m}_{1,ij}^r} \right]^2, \quad (50)$$

subject to $s_{ij}^M(\theta) = \hat{s}_{ij}, \quad j \in J_i \cup \{0\}, \quad \text{for every } i,$

over positive parameters θ . Dividing the transaction-level price sum in (15) by N yields $Q_N(\theta)$ plus a data-only constant, so both criteria give the same constrained minimizer.³⁷ The count weights give each transaction equal weight; dividing by the corresponding power of the relationship's average price puts both moment discrepancies in comparable, dimensionless units.

For each parameter trial, we approximate bidding on the cost and buyer-surplus grids in Table C.3.³⁸ We integrate Weibull costs over each cell, truncate the last active cell at δ_{ij} , and retain abstention above this cutoff. Suppressing the buyer index, let $\bar{c}_{jk}$ and c_{jk}^+ denote cell k 's conditional mean and upper cost. Supplier j can quote $b_{jq} = \delta_j - u_q$ at surplus nodes $0 \leq u_q \leq u_{jq}^+ = \delta_j - c_{jk}^+$, so each quote covers every cost in its cell. Let x_{jkq} denote its probability of choosing node q and $\Omega_{jq}(x_{-j})$ its winning probability. The buyer accepts zero-surplus quotes and splits ties equally among inside suppliers. We smooth best responses to expected profits $v_{jkq}(x) = (b_{jq} - \bar{c}_{jk})\Omega_{jq}(x_{-j})$ and update all suppliers simultaneously:

$$x_{jkq}^{BR}(x) = \frac{\Delta u_{jkq} \exp\{v_{jkq}(x)/\tau\}}{\sum_{h \in \mathcal{F}_{jk}} \Delta u_{jkh} \exp\{v_{jkh}(x)/\tau\}}, \quad (51)$$

$$x^{t+1} = (1 - \zeta)x^t + \zeta x^{BR}(x^t), \quad \zeta = \frac{1}{2},$$

where $\mathcal{F}_{jk}$ collects feasible nodes and Δu_{jkq} measures the interval each node represents.³⁹ At each temperature τ , we check the full undamped response error and use the converged solution to initialize the next, lower temperature. At the terminal temperature, we convert quotes back to monetary units and sum the joint probabilities ν_{ijq} of quoting b_{ijq} and winning:

$$s_{ij}^M = \sum_q \nu_{ijq}, \quad m_{r,ij}^M = \frac{\sum_q b_{ijq}^r \nu_{ijq}}{s_{ij}^M}, \quad r = 1, 2. \quad (52)$$

³⁷Expanding each squared discrepancy around $\hat{m}_{r,ij}$ eliminates the cross term because within-relationship residuals sum to zero. The remaining constant equals $C_N = N^{-1} \sum_i \sum_{j \in J_i} \sum_{a \in \mathcal{A}_{ij}^w} \sum_{r=1}^2 [((B_{ia}^w)^r - \hat{m}_{r,ij})/\hat{m}_{1,ij}^r]^2$.

³⁸Let $A = \lambda_{10}^C$, $\ell_{ij} = \lambda_{ij}/A$, $S_i = \sum_{j \in J_i} \ell_{ij}$, and $\eta_i = -\log \hat{s}_{i0}$. We divide monetary variables by AS_i and use the surplus bound $U_i = \max_j \{\ell_{ij} \eta_i^{1/\kappa}\}/S_i$. The cost-grid coordinate is $z = (c/\lambda_{ij})^\kappa$. We hold the grids and temperature schedule fixed within each buyer's share solve.

³⁹We use $\Delta u_{jkq} = \max\{0, \min(u_{jk}^+, u_{q+1}) - u_q\}$ and give the last grid endpoint zero weight. When $u_{jk}^+ = 0$, we assign probability one to $u = 0$, or $b = \delta_j$.

We obtain the outside share from the product of suppliers' abstention probabilities.

We estimate preferences and costs jointly through a nested search. Homogeneity lets us separate the monetary scale $A = \lambda_{10}^C$ from the relative coordinates $\phi = (\{\log(\lambda_g^C/A)\}_{g=1}^9, \log \kappa)$. At each trial ϕ , we set $A = 1$ and choose positive weights ω_{ij} that impose the outside share while matching inside-share ratios. For a reference supplier j_i^0 , we use

$$\begin{aligned} \delta_{ij} &= A \ell_{ij} (\eta_i \omega_{ij})^{1/\kappa}, \quad \omega_{ij} > 0, \quad \sum_{j \in J_i} \omega_{ij} = 1, \\ \log \frac{s_{ij}^M}{s_{ij_i^0}^M} &= \log \frac{\hat{s}_{ij}}{\hat{s}_{ij_i^0}}, \quad j \in J_i \setminus \{j_i^0\}. \end{aligned} \tag{53}$$

We solve in log weight ratios using safeguarded Broyden steps with a line search and a full Newton fallback. Nearby solutions supply starting values, but each preference trial requires a new bidding calculation. Let $\mu_{r,ij}(\phi)$ denote the resulting conditional price moments at $A = 1$. Scaling preferences and costs by A preserves shares and multiplies moment r by A^r , so we recover the monetary scale without another bidding calculation:

$$A(\phi) = \arg \min_{a>0} \sum_i \sum_{j \in J_i} \hat{\pi}_{ij} \sum_{r=1}^2 \left[\frac{a^r \mu_{r,ij}(\phi) - \hat{m}_{r,ij}}{\hat{m}_{1,ij}^r} \right]^2. \tag{54}$$

We profile A using the unique positive root of its cubic first-order condition, then minimize over ϕ using deterministic Nelder–Mead. We check errors against Table C.3's tolerances and reevaluate the final point from scratch. These checks concern the finite-grid, positive-temperature approximation; they do not establish a global minimum or continuous-equilibrium accuracy.

Table C.3: Numerical settings

Component	Setting
Cost grid	$z_k = \eta_i (k/64)^2, k = 0, \dots, 64$
Buyer-surplus grid	$u_q = U_i (q/320)^2, q = 0, \dots, 320$
Temperatures	$U_i \times (0.08, 0.04, 0.02, 0.01)$
Damping	$\zeta = 1/2$
Undamped response error	10^{-15}
Log share-ratio / absolute share error	$10^{-13} / 10^{-14}$
Simplex width / criterion spread	$2 \times 10^{-6} / 10^{-11}$

C.5 Standard errors

We calculate joint standard errors for preferences and costs, treating purchases as independent within and across buyers. We condition on each buyer's purchase count N_i , supplier roster, outside share, financing inputs, and cost-group assignments. For reference supplier j_i^0 , let y_i stack log share ratios $\log(\hat{s}_{ij}/\hat{s}_{ij_i^0})$ for $j \neq j_i^0$ and log price moments $\log \hat{m}_{r,ij}$ for $j \in J_i$ and $r = 1, 2$. Purchase a , with winner W_{ia} and price B_{ia}^w , contributes the influence vector

$$\begin{aligned}\psi_{ia}^{s,j} &= (1 - \hat{s}_{i0}) \left[\frac{\mathbf{1}\{W_{ia} = j\}}{\hat{s}_{ij}} - \frac{\mathbf{1}\{W_{ia} = j_i^0\}}{\hat{s}_{ij_i^0}} \right], \quad j \neq j_i^0, \\ \psi_{ia}^{m_{r,j}} &= \frac{(1 - \hat{s}_{i0})\mathbf{1}\{W_{ia} = j\}}{\hat{s}_{ij}} \left[\frac{(B_{ia}^w)^r}{\hat{m}_{r,ij}} - 1 \right], \quad j \in J_i, \quad r = 1, 2.\end{aligned}\tag{55}$$

With $\bar{\psi}_i = N_i^{-1} \sum_{a=1}^{N_i} \psi_{ia}$, we estimate

$$\hat{V}_{y_i} = \frac{1}{N_i(N_i - 1)} \sum_{a=1}^{N_i} (\psi_{ia} - \bar{\psi}_i)(\psi_{ia} - \bar{\psi}_i)', \quad \hat{V}_y = \text{blockdiag}_i(\hat{V}_{y_i}).\tag{56}$$

Here y stacks the buyer-specific vectors. This covariance captures variation in winning counts and both price moments and already includes the sample-size scaling.

We propagate this sampling variation through the share equations and the cost optimization. After substituting preferences that solve (53), we write the criterion as $Q_N(\beta, y)$ in the eleven cost coordinates $\beta = (\log A, \phi)'$ and define its score $F(\beta, y) = \frac{1}{2} \nabla_{\beta} Q_N(\beta, y)$. At an interior solution, $F(\hat{\beta}, y) = 0$. With $\mathcal{A} = \partial F / \partial \beta'$ and $\mathcal{B} = \partial F / \partial y'$, we obtain

$$D := \frac{\partial \hat{\beta}}{\partial y'} = -\mathcal{A}^{-1} \mathcal{B}.\tag{57}$$

Both derivatives include preferences' responses through the share equations. We retain the full criterion curvature in $\mathcal{A}$, including terms proportional to nonzero price discrepancies, and differentiate the empirical count weights and price normalizations in $\mathcal{B}$. Let $T(\beta, y)$ recover the ten cost scales, common shape, and 304 preferences in levels. Applying the chain rule gives

$$\begin{aligned}H &:= \frac{\partial \hat{\theta}}{\partial y'} = \frac{\partial T}{\partial \beta'} D + \frac{\partial T}{\partial y'}, \\ \hat{V}_{\theta} &= H \hat{V}_y H', \quad \text{se}(\hat{\theta}_k) = \sqrt{[\hat{V}_{\theta}]_{kk}}.\end{aligned}\tag{58}$$

We evaluate all derivatives at the estimates. The direct term $\partial T / \partial y'$ captures preferences' responses to shares even at fixed cost parameters. This calculation requires positive population shares, finite fourth price moments, a locally differentiable share inversion, and a nonsingular

score Jacobian. We do not report standard errors for the G5 estimates in Table C.2.

We differentiate the share equations implicitly and calculate criterion curvature from central differences of the resulting price gradients. Before taking differences, we apply one Newton correction for residual share-equation error and track the associated price correction separately. We check sensitivity to differentiation steps and solver tolerances, positivity of the relevant curvature matrices, and stability of active cost cells and feasible bids.⁴⁰ These checks assess numerical stability for the finite-grid, positive-temperature approximation; the standard errors measure sampling uncertainty conditional on that approximation.

C.6 Elasticities, markups, and willingness to pay

We calculate markups and implied price elasticities from model winning quotes b and financing-adjusted costs c . Let $W_{ij}(b)$ denote the supplier's winning probability holding rivals' strategies fixed. At an interior optimum in the continuous model,

$$\varepsilon_{ij}^p(b) = \frac{bW'_{ij}(b)}{W_{ij}(b)}, \quad \frac{b-c}{b} = -\frac{1}{\varepsilon_{ij}^p(b)}, \quad \frac{b-c}{c} = -\frac{1}{1 + \varepsilon_{ij}^p(b)}. \quad (59)$$

We therefore apply $-b/(b-c)$ to each model winning transaction to obtain its implied elasticity, and calculate its markup as $(b-c)/c$. Let H_{ij}^w denote the model's joint distribution of costs and quotes conditional on supplier j winning. For any transaction statistic $z_{ij}(c, b)$, we construct

$$G_z(t) = \sum_i \sum_{j \in J_i} \frac{n_{ij}}{N} \int \mathbf{1}\{z_{ij}(c, b) \leq t\} dH_{ij}^w(c, b), \quad N = \sum_i \sum_{j \in J_i} n_{ij}. \quad (60)$$

We report the median and quartiles of G_z , weighting relationships by their observed purchase counts and retaining the model's distribution within each relationship.⁴¹

⁴⁰We use outer and inner finite-difference steps of 5×10^{-7} and 5×10^{-8} , respectively, and a bidding-response tolerance of 10^{-15} . We halve the outer step, then also double the inner step; separately, we use response tolerance 10^{-14} . We compare curvature from differenced price gradients with second differences of price levels, retaining the Newton price correction as a separate component through both calculations. We require positive full, profiled, and independently reprofiled curvature, changes of at most 10% in standard errors and covariance-weighted parameter influences, and numerical score corrections of at most 0.1 standard errors. We also require derivative perturbations to preserve active cells and feasible actions.

⁴¹We use the same 304 relationships, 26 buyers, and 29,706 purchases throughout. In the notation of Appendix C.4, cost cell k and quote q contribute conditional winning mass $\Delta F_{ijk} x_{ijkq} \Omega_{ijq} / s_{ij}^M$, where ΔF_{ijk} denotes the Weibull probability of the active part of the cell. We integrate the continuous Weibull distribution within each cell when calculating margins and markups. We use $G_z^{-1}(p) = \inf\{t : G_z(t) \geq p\}$ for quantiles. For the supplier-count comparison, we restrict buyers to $|J_i| \leq 9$ or $|J_i| > 9$ and renormalize purchase-count weights within each group. We infer price elasticities from margins; we do not differentiate the finite-grid winning probabilities. The numerical policies need not satisfy the continuous first-order condition exactly.

To calculate the purchase response to costs, we multiply every supplier's financing-adjusted cost scale by a common factor $a > 0$, holding preferences, supplier rosters, and the Weibull shape fixed. Let $q_i = s_{i0}^M(\hat{\theta}) = \hat{s}_{i0}$ denote the baseline outside probability and $S_i(a)$ the probability of purchase after the change. The participation cutoff $c < \delta_{ij}$ and independent Weibull costs imply

$$q_i = \exp \left[- \sum_{j \in J_i} \left(\frac{\delta_{ij}}{\lambda_{ij}} \right)^\kappa \right], \quad S_i(a) = 1 - q_i^{a^{-\kappa}}. \quad (61)$$

Differentiating gives the local cost elasticity

$$\varepsilon_i^C = \left. \frac{\partial \log S_i(a)}{\partial \log a} \right|_{a=1} = \frac{\kappa q_i \log q_i}{1 - q_i}. \quad (62)$$

We weight buyers by N_i/N , where $N_i = \sum_j n_{ij}$, and obtain a median of -0.56 and an interquartile range of -0.68 to -0.47 . For a finite 1% cost reduction, we evaluate $S_i(0.99)$ and express the increase relative to either baseline purchases or forgone orders.⁴² This exercise measures the participation response to a common cost reduction; it does not assume that quotes fall in the same proportion.

We calculate willingness to pay by holding buyer surplus $u = \delta_{ij} - b$ fixed as the supplier's valuation changes. The compensating quote change satisfies

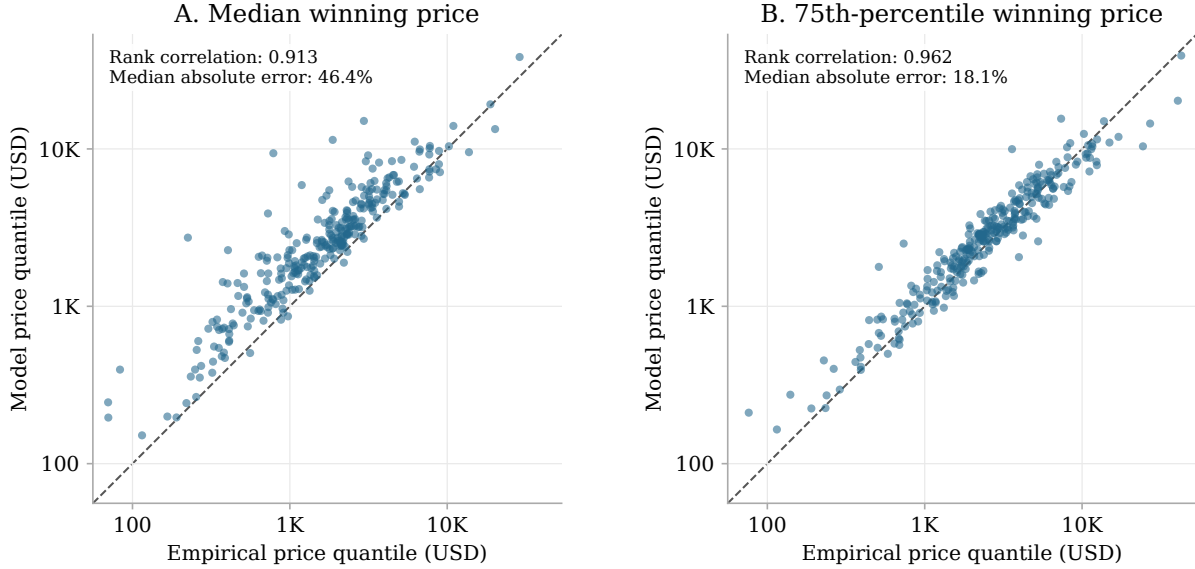
$$db = d\delta_{ij}, \quad \varepsilon_{ij}^{\text{comp}}(b) = \left. \frac{d \log b}{d \log \delta_{ij}} \right|_u = \frac{\delta_{ij}}{b}. \quad (63)$$

We evaluate this ratio at model winning prices and use (60) to aggregate it, giving a median of 1.17 and an interquartile range of 1.07–1.33. We calculate each ratio before taking quantiles, preserving price variation within relationships. This elasticity measures compensation for a proportional increase in the buyer's monetary valuation of a supplier; it does not describe how equilibrium quotes respond to that change. Figure 5 illustrates the estimated costs and valuations at the relationship level.⁴³

⁴²We use $\kappa = 1.9091095682$. At the purchase-count-weighted median outside probability, $q_i = 0.1102482027$, we obtain $S_i(1) = 0.8897517973$ and $S_i(0.99) = 0.8943620636$. Thus, $100[S_i(0.99) - S_i(1)]/S_i(1) = 0.5182\%$, while $100[S_i(0.99) - S_i(1)]/q_i = 4.1817\%$. The absolute elasticity and relative purchase expansion increase with q_i , so we obtain their quantiles by transforming the purchase-count-weighted quantiles of outside shares. This response depends on the estimated shape and the supplied outside shares that we match in estimation.

⁴³We give each of the 304 relationships equal weight in this figure. Panel A compares $\int c dH_{ij}^w(c, b)$ with the observed mean winning price $\hat{m}_{1,ij}$; panel B compares δ_{ij}/λ_{ij} with n_{ij}/N_i . We fit local-linear curves using tricube weights and the nearest 40% of relationships. We estimate the cost density with Gaussian kernels in log mean winning costs, then transform back with the inverse-cost Jacobian. We reflect Gaussian kernels at zero for the density of δ_{ij}/λ_{ij} . Panel A's limits of \$7,500 for costs and \$10,000 for prices hide eight relationships; we retain all 304 when fitting the curves and densities.

Figure C.1: Median and upper-quartile winning prices across relationships



Notes: Each point represents one of 304 buyer–supplier relationships in the estimation sample. Panel A compares empirical and model median winning prices; panel B compares their 75th percentiles. Both quantiles condition on the indicated supplier winning. We do not target either quantile in estimation. Dashed lines indicate equality, and both axes use logarithmic scales. We give each relationship equal weight in the reported statistics. Rank correlations use Spearman’s measure with average ranks for ties. We calculate each absolute percentage error relative to the empirical quantile. We calculate empirical quantiles by linear interpolation and model quantiles from the generalized inverse of each conditional model CDF. The within-buyer correlations in Section 5.5 use Pearson’s measure after we subtract each buyer’s mean log quantile from the log quantiles of its relationships. We convert pesos at 1,000 CLP per USD.

Table C.4 relates estimated preferences to supplier characteristics across all 304 buyer–supplier relationships. We regress $100\hat{\delta}_{ij}/\bar{\delta}$ on these characteristics, where $\bar{\delta} = \$3,662.47$ denotes the purchase-count-weighted mean preference. We give relationships equal weight and add buyer fixed effects in column 5. We construct billing and customer measures from January 2, 2019–March 9, 2026 invoices, excluding sales to the focal buyer. Monthly billing divides other-customer billing by the calendar-month span between the supplier’s first and last observed invoices, including gaps. We measure the customer base through the logarithm of one plus the other-buyer count and the largest other customer’s share of billing. The same-province indicator equals one when the supplier and buyer share a province. The same-sector share divides billing to other customers in the buyer’s two-digit sector by other-customer billing with known sector information. The repeat-customer share measures billing attributable to customers receiving invoices in at least six distinct months. Billing continuity measures the fraction of months with other-customer billing. We also include firm age in

Table C.4: Supplier characteristics and estimated preferences

	(1) Scale and age	(2) Customer base	(3) Buyer–supplier match	(4) Trading history	(5) Trading history + buyer FE
Log monthly billing to other buyers	0.29 (3.67)	10.67 (4.69)	10.73 (4.50)	26.82 (7.10)	23.59 (6.76)
Firm age (10 years)	29.38 (39.32)	22.54 (37.46)	13.65 (39.57)	9.31 (38.41)	23.60 (34.70)
Firm age squared	-3.81 (11.59)	0.47 (11.89)	3.50 (12.36)	4.56 (11.27)	-2.28 (10.09)
Log(1 + other-buyer count)		-28.81 (13.77)	-27.14 (10.49)	-28.15 (11.14)	-13.72 (10.18)
Largest other-customer billing share		-28.39 (44.31)	-30.90 (38.66)	-19.22 (31.00)	3.95 (28.05)
Same province as buyer			-0.00 (10.81)	3.17 (9.97)	-24.80 (9.97)
Same-sector billing share			-37.53 (27.80)	-35.54 (33.64)	15.76 (40.06)
Repeat-customer billing share				-73.21 (23.39)	-77.47 (25.78)
Billing continuity				-86.20 (38.41)	-36.58 (31.43)
Buyer fixed effects	No	No	No	No	Yes
Relationships	304	304	304	304	304
Buyers	26	26	26	26	26
R^2	0.013	0.046	0.089	0.159	0.366
Within-buyer R^2					0.161

Notes: We use all 304 relationships and 26 buyers in the current ten-group estimation sample, with equal relationship weights. The dependent variable equals 100 times each preference estimate divided by the invoice-count-weighted mean preference across these relationships. Columns 1–4 include an intercept; column 5 includes buyer fixed effects. Every column controls for recorded-history length and no observed other buyers. Columns 3–5 also control for missing province and sector information and the classified share of other-customer billing. All sales and trading measures exclude the focal buyer and use January 2, 2019–March 9, 2026. Shares run from zero to one. Repeat customers receive invoices in at least six distinct months. We measure firm age in decades as of March 9, 2026. Parentheses report buyer-clustered CR1 standard errors; they do not incorporate uncertainty from structural estimation. We interpret coefficients as descriptive associations.

decades as of March 9, 2026, its square, and measurement controls.⁴⁴ Column 5’s coefficient on log monthly billing implies that doubling billing to other customers corresponds to a preference difference of

$$23.5912 \times \log(2) \times \frac{\$3,662.47}{100} = \$598.89.$$

The model’s price coefficient of minus one translates this difference into approximately \$600 in additional willingness to pay per order, holding buyer fixed effects and other covariates constant. We interpret this comparison as a descriptive association.

⁴⁴All columns control for log recorded-history length and no observed other buyers. Columns 3–5 also control for missing province and sector information and the classified share of other-customer billing. We center log billing, assign zero to undefined logs and shares, and retain corresponding indicators. Recorded history spans the supplier’s first and last invoices to any buyer within the sample window. We report buyer-clustered CR1 standard errors conditional on the structural estimates.

C.7 Markups over variable costs in the INE road-freight survey

We use the public CSV releases of INE’s *Encuesta Estructural de Transporte de Carga por Carretera* (ETRANC) for 2019–2023.⁴⁵ Our sample contains 2,217 observations across the five annual releases. We exclude the five records associated with a survey identifier that reports an extreme operating-lease expense for movable assets in 2019; retaining these records gives markups of 30.7% and 36.2% under the two expense definitions below. We multiply the 2019–2020 amounts by the supplied expansion factors and use the already expanded 2021–2023 amounts directly. We verify this treatment against six published aggregates for each year before applying the sample exclusion.

For each firm f and year t , we take road-freight revenue R_{ft} from survey item B130. We construct a base non-labor expense measure V_{ft} by summing fuel and lubricants, vehicle parts and tires, tolls and weighing, terminal and parking charges, loading and unloading, maintenance, subcontracted freight, storage, packaging, commissions, shipment-related non-recoverable taxes, and import and export expenses.⁴⁶ We add direct labor compensation L_{ft} , comprising gross wages, other remuneration, and employer contributions (C188, C189, and C190), in both expense definitions.

Our first measure, $C_{ft}^{(3)}$, adds three categories to $V_{ft} + L_{ft}$: other operating inputs (E126), representation and travel allowances (E412), and vehicle rentals without a driver (E314). It excludes other operating expenses not specified elsewhere (E414). Our second measure, $C_{ft}^{(4)}$, includes all four categories by also adding E414. Both definitions exclude separately reported premises rent, insurance, depreciation, and financing expenses. These annual categories can mix expenses that increase with an additional freight job with overhead or existing capacity commitments; the public data do not separate these uses.

For each cost measure $C \in \{C^{(3)}, C^{(4)}\}$, we pool revenues and expenses across the observations in the sample $\mathcal{S}$ and calculate

$$\mu^{\text{INE}}(C) = \frac{\sum_{(f,t) \in \mathcal{S}} (R_{ft} - C_{ft})}{\sum_{(f,t) \in \mathcal{S}} C_{ft}}. \quad (64)$$

The three-category expenses equal 73.42% of pooled road-freight revenue and yield a markup of 36.2%. Including E414 as well raises the expense share to 76.52% and lowers the markup

⁴⁵INE provides the releases and supporting documentation through its [ETRANC data catalogue](#). The catalogue lists data through 2023 as of October 24, 2026.

⁴⁶We sum items E103, E114, E121, E122, E128, E2041, E2042, E209, E301, E3021, E3022, E3081, E3082, E316, E411, E423, E440, E512, and E513. The releases for 2020–2023 omit E513; we assign zero to that absent item.

to 30.7%. We use the unrounded totals in both calculations. These ratios aggregate nominal revenues and expenses before division; they do not average firm-level or annual markups. The 30.7–36.2% range reflects the choice of expense definition, rather than statistical bounds on marginal-cost markups.

We use these aggregate accounting measures as external benchmarks for the magnitude of markups. Annual expenses do not isolate the cost of one additional freight job; in particular, some direct labor payments need not vary with that job. The main text instead reports the median transaction markup from the model and includes financing in marginal cost.

D Identification Proofs

D.1 Nonparametric identification

Theorem 2 (Nonparametric identification). *Fix buyer i , its environment $\mathcal{E}_i$, and a finite known roster J_i with $|J_i| \geq 2$. Maintain A1–A2 and outside utility zero, including one fixed pure equilibrium with continuous, strictly increasing strategies on the active cost intervals.*

Let B_{ia}^w denote the winning nominal bid when a transaction occurs. The econometrician observes the full population objects

$$\begin{aligned} \tilde{s}_{ij} &= \Pr(j^*(a) = j \mid j^*(a) \neq 0, \mathcal{E}_i), \\ L_{ij}(p) &= \Pr(B_{ia}^w \leq p \mid j^*(a) = j, \mathcal{E}_i), \quad j \in J_i. \end{aligned} \tag{65}$$

These observations identify every absolute taste:

$$\delta_{ij} = \text{ess sup}(B_{ia}^w \mid j^*(a) = j, \mathcal{E}_i). \tag{66}$$

If the econometrician also knows the exact finite essential lower cost endpoint of one designated supplier, the observations identify q_{i0} , the unconditional CDF $F_{ij}^C(c)$ for every $c \leq \delta_{ij}$, every lower cost endpoint, and every inactive probability

$$r_{ij} = 1 - F_{ij}^C(\delta_{ij}).$$

Knowledge of q_{i0} can replace knowledge of an exact cost floor.

Without additional restrictions on the upper tails, the observations do not identify the conditional distributions

$$H_{ij}^+(c) = \Pr(C_{ija} \leq c \mid C_{ija} > \delta_{ij}, \mathcal{E}_i), \quad c > \delta_{ij}.$$

Nonnegativity alone does not replace the exact known cost-floor condition or otherwise ensure identification of q_{i0} and the active cost CDFs in this unrestricted class.

Proof. Fix buyer i and its environment. Suppress i , a , and $\mathcal{E}_i$: write C_j , σ_j , F_j^C , and δ_j for supplier j 's cost, nominal strategy, cost CDF, and taste. Write $d_j = \underline{c}_{ij}$, $W = j^*(a)$, and B^w for the winning nominal bid. Set $\pi = 1 - q_0$. We first derive identities for an arbitrary admissible primitive/equilibrium pair; we do not treat its π as observed.

1. Participation, price endpoints, and active bid laws. The bidding theorem in Section 4 and its proof give

$$r_j = 1 - F_j^C(\delta_j) \in (0, 1), \quad q_0 = \prod_j r_j \in (0, 1), \quad r_{-j} := \prod_{k \neq j} r_k > 0.$$

Every acceptable bid wins whenever all rivals abstain. Every active type satisfies

$$c < \sigma_j(c) < \delta_j, \quad \lim_{c \uparrow \delta_j} \sigma_j(c) = \delta_j.$$

Types above δ_j abstain almost surely.

Represent an acceptable bid by $X_j = B_j - \delta_j$ and represent inactivity by $X_j = +\infty$. A1 and the fixed pure strategy profile make the X_j independent. Strictly increasing active strategies, atomless active costs, and the absence of cost atoms at d_j and δ_j imply that X_j has no finite atoms. Atoms in the inactive cost tail contribute only to the probability at $+\infty$.

The model appendix also extends global optimality from cost-almost every type to every interior active type. Optimizing types are dense because every open active cost interval has positive probability. Continuity of the strategy and atomlessness of rivals' acceptable bids allow the best-response inequalities to pass to the limit. We therefore use global incentive inequalities pointwise below.

For sufficiently small $\varepsilon > 0$, costs in $(\delta_j - \varepsilon, \delta_j)$ have positive probability. Those types bid above $\delta_j - \varepsilon$ and win with probability at least r_{-j} . Hence

$$\Pr(W = j, B^w > \delta_j - \varepsilon) \geq r_{-j} [F_j^C(\delta_j) - F_j^C(\delta_j - \varepsilon)] > 0.$$

The acceptance rule bounds every winning bid by δ_j . This proves (66) and also gives $\tilde{s}_j > 0$ for every supplier.

Define the observable lower winning-price endpoint and the active effective-price interval:

$$\underline{p}_j = \text{ess inf}(B^w \mid W = j), \quad \ell_j = \underline{p}_j - \delta_j, \quad I_j = (\ell_j, 0).$$

Every accepted bid wins with probability at least r_{-j} , so the marginal active bid law and the winning-price law have the same support endpoints. Continuity and strict increase therefore make $c \mapsto \sigma_j(c) - \delta_j$ a bijection from (d_j, δ_j) onto I_j , with $-\infty < \ell_j < 0$.

Let $c_j(x)$ denote its continuous inverse and define

$$\mu_j(x) = \delta_j + x - c_j(x) > 0, \quad x \in I_j.$$

Then

$$\lim_{x \downarrow \ell_j} c_j(x) = d_j, \quad \lim_{x \uparrow 0} c_j(x) = \delta_j.$$

2. Global incentives supply the required differentiability. For $x \leq 0$, define the unconditional bid CDFs and survivals

$$G_j(x) = \Pr(X_j \leq x), \quad S_j(x) = 1 - G_j(x), \quad Q_{-j}(x) = \prod_{k \neq j} S_k(x).$$

These functions are continuous, and $S_j(x) \geq r_j > 0$. An acceptable nominal bid $\delta_j + x$ wins with probability $Q_{-j}(x)$ because finite bid ties have probability zero.

Fix $x, x+h \in I_j$ with $h > 0$. The two types $c_j(x)$ and $c_j(x+h)$ can submit each other's equilibrium bids. Their global best-response inequalities give

$$\begin{aligned} \mu_j(x)Q_{-j}(x) &\geq [\mu_j(x) + h]Q_{-j}(x+h), \\ \mu_j(x+h)Q_{-j}(x+h) &\geq [\mu_j(x+h) - h]Q_{-j}(x). \end{aligned}$$

Rearranging yields

$$-\frac{Q_{-j}(x)}{\mu_j(x+h)} \leq \frac{Q_{-j}(x+h) - Q_{-j}(x)}{h} \leq -\frac{Q_{-j}(x+h)}{\mu_j(x)}.$$

Continuity gives the right derivative. Applying the same inequalities to $x-h, x$ gives the identical left derivative. Thus

$$Q_{-j} \in C^1(I_j), \quad Q'_{-j}(x) = -\frac{Q_{-j}(x)}{\mu_j(x)}. \quad (67)$$

We derive this identity from global optimality without assuming a derivative of σ_j . It holds throughout I_j , including any rival's entry point in that interval.

3. Observable measures and the Stieltjes inversion. After identifying tastes, construct the observable conditional effective-price sub-CDFs

$$D_j(x) = \tilde{s}_j L_j(x + \delta_j), \quad A(x) = \sum_j D_j(x), \quad T_{-j}(x) = \sum_{k \neq j} D_k(x). \quad (68)$$

They are continuous for $x \leq 0$, and $A(0) = 1$. For any admissible pair with transaction probability π ,

$$R(x) := 1 - \pi A(x) = \prod_j S_j(x) \geq q_0 > 0, \quad x \leq 0. \quad (69)$$

Indeed, $\pi A(x)$ is the unconditional probability that the smallest effective bid is at most x . Independence applies before conditioning on a transaction.

Independence and the absence of finite bid atoms give the following identities of Lebesgue–Stieltjes measures on $(-\infty, 0]$:

$$\pi dD_j(x) = Q_{-j}(x) dG_j(x), \quad \frac{\pi dD_j(x)}{R(x)} = -d \log S_j(x). \quad (70)$$

The first identity weights supplier j 's bid measure by the probability that every rival bids above it. For the second, divide by $R = S_j Q_{-j}$ and use $dG_j = -dS_j$. The continuous bounded-variation chain rule applies because $S_j \geq r_j > 0$.

Since $S_j = 1$ below its finite lower endpoint, integration gives

$$S_j(x) = \exp \left\{ -\pi \int_{(-\infty, x]} \frac{dD_j(t)}{1 - \pi A(t)} \right\}, \quad x < 0. \quad (71)$$

Thus a given π determines every unconditional bid survival. These survivals retain the inactive probabilities; we do not renormalize the bid laws conditional on participation.

Summing (70) over $k \neq j$ and using (67) gives, on I_j ,

$$\pi dT_{-j} = -R d \log Q_{-j} = \frac{R(x)}{\mu_j(x)} dx.$$

The final density is continuous. Equivalently, for $u < v$ in I_j ,

$$T_{-j}(v) - T_{-j}(u) = \frac{1}{\pi} \int_u^v \frac{R(x)}{\mu_j(x)} dx.$$

Consequently the observed CDF sum itself satisfies

$$T_{-j} \in C^1(I_j), \quad T'_{-j}(x) = \frac{1 - \pi A(x)}{\pi \mu_j(x)} > 0. \quad (72)$$

This is an ordinary continuous derivative, so the proof requires no choice of an almost-everywhere density version. We have not assumed that individual bid CDFs have densities.

4. Cost recovery for a given transaction probability. Rearranging (72) gives

$$\begin{aligned} c_j(x) &= \delta_j + x - \frac{1 - \pi A(x)}{\pi T'_{-j}(x)}, \\ F_j^C(c_j(x)) &= 1 - S_j(x), \quad x \in I_j. \end{aligned} \tag{73}$$

The second identity follows from the increasing active strategy: $X_j \leq x$ exactly when $C_j \leq c_j(x)$, up to null events. The inverse c_j covers the whole interval (d_j, δ_j) . Its lower limit identifies d_j , and

$$r_j = S_j(0-), \quad F_j^C(\delta_j) = 1 - r_j.$$

The no-atom assumptions give $F_j^C(d_j) = 0$ and continuity at δ_j ; the CDF equals zero below d_j . Equations (71)–(73) therefore recover the unconditional cost CDF through δ_j whenever the econometrician knows π .

5. An exact known floor identifies the transaction probability. First establish a strictly positive limiting markup at each lower bid endpoint. The feasible fixed bid

$$b_j^* = \frac{d_j + \delta_j}{2}$$

earns at least

$$K_j := \frac{\delta_j - d_j}{4} r_{-j} > 0$$

for every $d_j < c < d_j + (\delta_j - d_j)/4$. Global optimality makes equilibrium profit at least K_j . Since winning probability is at most one, the equilibrium markup is also at least K_j . Taking the lower-endpoint limit gives

$$\underline{p}_j - d_j \geq K_j > 0. \tag{74}$$

This limit is finite because $\underline{p}_j < \delta_j < \infty$. The argument does not use a limiting cost density at d_j .

Define a boundary quantity directly from the observed CDF sum:

$$D_{-j} := \lim_{h \downarrow 0} \frac{T_{-j}(\ell_j + h) - T_{-j}(\ell_j)}{h}. \tag{75}$$

We now prove that this right derivative exists and lies in $(0, \infty)$. As $x \downarrow \ell_j$,

$$\mu_j(x) \longrightarrow \underline{p}_j - d_j > 0, \quad R(x) \longrightarrow 1 - \pi A(\ell_j) \geq q_0 > 0.$$

Equation (72) therefore gives

$$\lim_{x \downarrow \ell_j} T'_{-j}(x) = \frac{1 - \pi A(\ell_j)}{\pi(\underline{p}_j - d_j)} \in (0, \infty).$$

Continuity of T_{-j} at ℓ_j and the mean value theorem on $[\ell_j, \ell_j + h]$ show that this limit equals the right derivative in (75). Solving the resulting identity for π yields

$$\pi = \frac{1}{A(\ell_j) + (\underline{p}_j - d_j)D_{-j}}, \quad q_0 = 1 - \pi. \quad (76)$$

For a supplier with an exact known d_j , the right-hand side uses only that floor and transaction-conditional observations. The endpoint ℓ_j and the function T_{-j} do not depend on an assumed unconditional sampling scale. We used an admissible pair's own π to prove existence of the observable right derivative, then solved for that π .

The argument allows heterogeneous lower bid endpoints and coincident entry points. It uses continuity at ℓ_j and differentiability strictly to its right, not a left derivative or individual endpoint densities. It also imposes no finite bid-density limit at the upper endpoint 0.

If the econometrician knows several floors, each must yield the same value in (76). In particular, when every $d_j = 0$,

$$A(\ell_j) + \underline{p}_j D_{-j} = \frac{1}{\pi} \quad \text{for every } j. \quad (77)$$

An exact zero floor requires positive cost probability arbitrarily close to zero. The inequality $C_j \geq 0$ alone does not justify substituting $d_j = 0$ in (76).

6. Nonnegativity alone does not determine the missing scale. The following two-supplier example establishes this qualification within the maintained equilibrium class. Set $\delta_1 = \delta_2 = 1$. For $v \in [1/2, 1)$, write $q = 1 - v$. For nominal bids $8/9 < b < 1$, define

$$z(b) = 3\sqrt{1 - b}, \quad H_v(b) = \sqrt{q + vz(b)}, \quad c_v(b) = 1 - \frac{5}{9}z(b)^2 - \frac{4q}{9v}z(b).$$

Here H_v will be a supplier's unconditional nominal-bid survival, including inactivity. Direct calculation gives

$$c'_v(b) = 5 + \frac{2q}{vz(b)} > 0, \quad c_v(8/9+) = d_v := \frac{8}{9} - \frac{4}{9v} \geq 0, \quad c_v(1-) = 1.$$

Define identical independent cost laws by

$$F_v^C(c) = 0 \quad (c \leq d_v), \quad F_v^C(c_v(b)) = 1 - H_v(b) \quad (8/9 < b < 1),$$

and

$$F_v^C(c) = 1 - \sqrt{q} e^{-(c-1)} \quad (c \geq 1).$$

These laws have no atoms at d_v or 1, have positive continuous density $-H'_v(b)/c'_v(b)$ on the active cost interval, and assign probability $\sqrt{q} > 0$ above 1.

Let each supplier use $\sigma_v = c_v^{-1}$ on $(d_v, 1)$ and abstain above 1. Against this strategy, an active-range bid wins with probability $H_v(b)$. The identity $c_v(b) = b + H_v(b)/H'_v(b)$ gives

$$\frac{d}{db}[(b - c)H_v(b)] = H'_v(b)[c_v(b) - c].$$

Since $H'_v < 0$ and c_v strictly increases, profit increases up to $b = \sigma_v(c)$ and decreases thereafter. Bids below $8/9$ win surely and yield profit increasing in the bid; the comparison at $b = 1$ follows by continuity. Rejected bids and abstention yield zero. The prescribed active bid earns positive profit, and types above 1 cannot profit from an acceptable bid. Thus these strategies form a global pure equilibrium in the maintained class.

Independence gives $q_0 = H_v(1-)^2 = q$ and, for $8/9 < b < 1$,

$$\Pr(W \neq 0, B^w \leq b) = 1 - H_v(b)^2 = v[1 - z(b)].$$

Symmetry therefore gives the same observations for every v :

$$\tilde{s}_1 = \tilde{s}_2 = \frac{1}{2}, \quad L_1(b) = L_2(b) = 1 - z(b), \quad 8/9 < b < 1,$$

with CDF values zero below $8/9$ and one at and above 1. Yet $v = 1/2$ gives $(q_0, d_v) = (1/2, 0)$, whereas $v = 3/4$ gives $(q_0, d_v) = (1/4, 8/27)$. Both economies have nonnegative costs. Thus nonnegativity alone does not identify q_0 or the unrestricted active cost laws.

7. Identification across admissible pairs and remaining tails. Consider any two admissible primitive/equilibrium pairs with the same observations and the same designated

known exact floor. Equation (66) first gives the same tastes, hence the same D_j , A , T_{-j} , $\underline{p}_j$, and ℓ_j . The right derivative (75) is a functional of these common observed CDFs. Equation (76) therefore gives the same π in both pairs. If the econometrician instead knows q_0 , the common known value directly supplies the same π . Equations (71) and (73) then give the same bid survivals, inverse active strategies, lower cost endpoints, active cost CDFs, and inactive probabilities. This comparison allows each pair to use its own fixed equilibrium in the class; it does not require equilibrium uniqueness.

Finally, in the unrestricted class, hold all tastes and all cost-CDF values through δ_j fixed. For $c > \delta_j$, replace the tail by

$$\hat{F}_j^C(c) = F_j^C(\delta_j) + r_j U_j(c),$$

where U_j is any proper conditional CDF supported strictly above δ_j , with $U_j(\delta_j+) = 0$. Choose the new costs independently, keep the active strategies unchanged, and let the new high-cost types abstain. Active types face the same rival bid laws and inactivity probabilities, so their global best responses remain unchanged. High-cost types cannot profit from an acceptable bid. Different choices of U_j therefore produce admissible equilibria with the same observations and the same q_0 , while changing the conditional upper cost tails. $\square$

D.2 Identification under global family restrictions

Proposition 1 (Identification within a known family). *Maintain the assumptions under which Theorem 2 identifies the unconditional cost CDF through each taste cutoff. Suppose each full cost CDF belongs to a known family $\mathcal{F}_{ij}$ compatible with the maintained primitive conditions.*

At the identified cutoff δ_{ij} , suppose this family satisfies

$$\begin{aligned} F, G \in \mathcal{F}_{ij}, \quad F(c) = G(c) \quad \text{for every } c \leq \delta_{ij} \\ \implies \quad F(c) = G(c) \quad \text{for every } c \in \mathbb{R}. \end{aligned} \tag{78}$$

Then the observations identify the full cost CDF F_{ij}^C , including its conditional upper tail.

If $\mathcal{F}_{ij} = \{F(\cdot; \theta) : \theta \in \Theta_{ij}\}$ and the parameterization also satisfies

$$F(\cdot; \theta) = F(\cdot; \theta') \implies \theta = \theta',$$

the observations identify θ .

Corollary 1 (Weibull costs with shape two). *Fix the buyer environment and known roster*

with $|J_i| \geq 2$ as in Theorem 2. Maintain A1–A2, outside utility zero, and the observation scheme in (65). Suppose costs are nonnegative and satisfy the global restriction

$$F_{ij}^C(c) = 1 - \exp[-(c/\lambda_{ij})^2], \quad c \geq 0, \quad \lambda_{ij} \in (0, \infty). \quad (79)$$

Every member of this family has exact lower endpoint zero. Transaction-only observations therefore identify all tastes, q_{i0} , and all scales, with

$$\lambda_{ij} = \frac{\delta_{ij}}{\sqrt{-\log r_{ij}}}. \quad (80)$$

They consequently determine the full cost laws within this family.

Proof of Proposition 1. Consider two admissible primitive/equilibrium pairs with the same observations and the same auxiliary information required by Theorem 2. That theorem gives the same taste δ_{ij} and the same unconditional CDF values for every $c \leq \delta_{ij}$. Condition (78) therefore forces the two full CDFs to coincide. An injective parameterization then forces their parameters to coincide. $\square$

Proof of Corollary 1. For every $\lambda_{ij} \in (0, \infty)$, the stated family satisfies

$$F_{ij}^C(0) = 0, \quad F_{ij}^C(\varepsilon) > 0 \quad \text{for every } \varepsilon > 0.$$

Thus zero is the exact essential lower endpoint independently of the unknown scale. Theorem 2 identifies δ_{ij} , q_{i0} , the active CDF, and $r_{ij} \in (0, 1)$.

The global Weibull restriction gives

$$r_{ij} = \exp[-(\delta_{ij}/\lambda_{ij})^2].$$

Solving this equation yields (80). Since $\delta_{ij} > 0$ and $0 < r_{ij} < 1$, the formula gives one finite positive scale. Two family members agreeing through the cutoff therefore have the same scale and the same full CDF. This verifies both the continuation condition and parameter uniqueness for the shape-two family. $\square$

Corollary 2 (Standard Weibull costs with unknown shape and scale). *Fix the buyer environment and known roster with $|J_i| \geq 2$ as in Theorem 2. Maintain A1–A2, outside utility zero, and the full transaction-data observation scheme. Suppose costs follow the global, unshifted*

Weibull family

$$F_{ij}^C(c) = 1 - \exp[-(c/\lambda_{ij})^{\kappa_{ij}}], \quad c \geq 0, \quad \lambda_{ij}, \kappa_{ij} \in (0, \infty).$$

Then the observations identify every taste, q_{i0} , both Weibull parameters for every supplier, and the full cost laws.

More specifically, knowledge of the unconditional cost CDF on any nonempty open interval contained in $(0, \delta_{ij})$ identifies λ_{ij} and κ_{ij} within this family.

Proof. Every member of the standard unshifted family has exact lower endpoint zero, no atom there or at a finite positive cutoff, a continuous strictly positive density on $(0, \delta_{ij})$, and positive probability above δ_{ij} . The endpoint density may vanish or diverge; A2 imposes its density condition only on the open active interval. Every member also satisfies A2(iii), as Appendix B.1 shows, so Theorem 1 establishes equilibrium existence. Theorem 2 therefore supplies the unconditional active cost CDF and the other nonparametric objects.

Suppress i, j for the parameter argument. Choose two distinct points $0 < c_1 < c_2$ in an identified open active interval. Set

$$H_m = -\log(1 - F^C(c_m)) > 0, \quad Y_m = \log H_m, \quad m = 1, 2.$$

The Weibull formula gives

$$Y_m = \kappa \log c_m - \kappa \log \lambda.$$

Subtracting the two equations and then substituting back yields

$$\kappa = \frac{Y_2 - Y_1}{\log c_2 - \log c_1}, \quad \lambda = c_1 H_1^{-1/\kappa}. \quad (81)$$

These expressions have finite values because $0 < F^C(c_1) < F^C(c_2) < 1$.

If two parameter pairs agree on the active interval, (81) gives the same parameters and hence the same full CDF. We use two unconditional cost-CDF values after the first theorem recovers that CDF from the full winning-price distributions. $\square$

Interpretation and scope. The first theorem identifies the total inactive probability. The global family restriction determines how that probability spreads across costs above the cutoff. This gives full-distribution identification within the maintained family, although unrestricted alternative tails can generate the same observations.

Appendix D.2 proves the family and Weibull results and extends the Weibull argument to unknown shape and scale.

Invoices need not record no-purchase events: the known-floor version recovers their probability from transaction-conditional distributions. An exact zero floor means that costs place positive probability arbitrarily close to zero; the inequality $C_{ija} \geq 0$ alone does not supply that information.

Theorem 1 establishes the existence of an equilibrium in the stated class. We compare admissible primitive/equilibrium pairs without requiring equilibrium uniqueness. We maintain one fixed profile within each buyer environment and do not cover an unobserved common mixture over profiles.

These results use exact population distributions. They do not establish identification from the estimator's finite vector of shares and mean winning bids, or show that its finite-grid, entropy-smoothed solution implements the continuous-game equilibrium. Sample extrema generally differ from population endpoints, and measurement error can alter price supports. Finite, noisy invoice data require separate statistical arguments.

D.3 Bid recovery with two suppliers

Fix buyer i with two suppliers and take preferences and the outside probability q_{i0} as given. Define $X_j = B_j - \delta_{ij}$, with $X_j = +\infty$ when supplier j abstains, and write $S_j(x) = \Pr(X_j > x)$. For this density illustration, let $g_j(x)$ denote the density of finite adjusted quotes. For $x < 0$, let $h_j(x)$ denote the unconditional joint density of supplier j winning at adjusted quote x , and let $R(x)$ denote the probability that both adjusted quotes exceed x , including abstention. With $\pi = 1 - q_{i0}$, transaction-conditional winning shares $\tilde{s}_{ij}$, and conditional winning-price CDFs L_{ij} , the observations determine $h_j(x) = \pi \tilde{s}_{ij} L'_{ij}(x + \delta_{ij})$ and $R(x) = 1 - \pi \sum_{j=1}^2 \tilde{s}_{ij} L_{ij}(x + \delta_{ij})$.

Independence before conditioning on a transaction gives

$$h_1(x) = g_1(x)S_2(x), \quad R(x) = S_1(x)S_2(x).$$

The first expression weights supplier 1's quote density by the probability that supplier 2 quotes more or abstains. Both expressions contain the same rival-survival factor. Taking their ratio cancels it:

$$\frac{h_1(x)}{R(x)} = \frac{g_1(x)S_2(x)}{S_1(x)S_2(x)} = \frac{g_1(x)}{S_1(x)} = -\frac{d}{dx} \log S_1(x).$$

We integrate from below supplier 1's lowest finite quote, where $S_1 = 1$, to obtain $S_1(x) = \exp\{-\int_{-\infty}^x h_1(t)/R(t) dt\}$. Swapping supplier identities recovers S_2 ; the limit $S_j(0-)$ retains supplier j 's abstention probability. Appendix D.1 gives the general measure-based inversion.

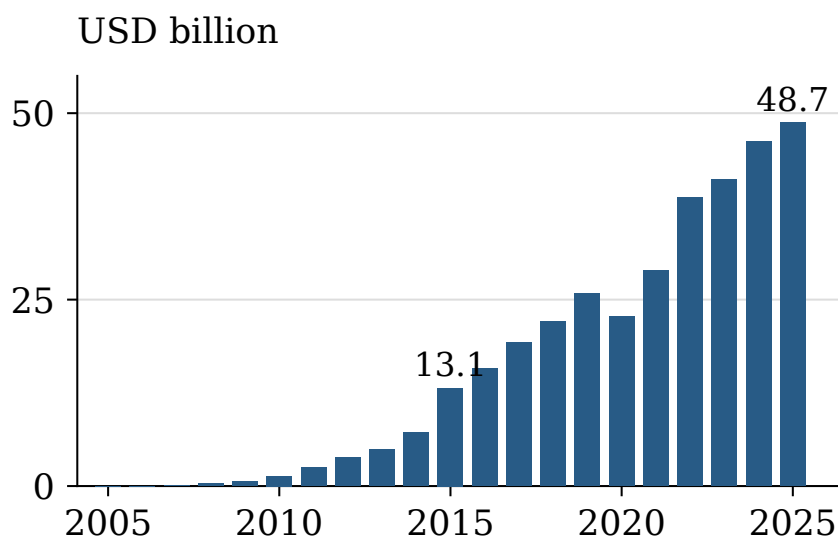
Preferences shift the quote thresholds but leave this cancellation intact. For $b < \delta_{i1}$, the

recovered rival survival gives the model’s winning probability, $W_{i1}(b) = S_2(b - \delta_{i1})$. On the active bid support, the pricing first-order condition then recovers cost as $c = b + W_{i1}(b)/W'_{i1}(b)$; the same argument applies to supplier 2.

E Applicant Data and Additional Descriptive Statistics

This appendix reports sample definitions, coverage, and additional descriptive evidence for Section 2.

Figure E.1: Total annual volume factored in Chile



Notes: The figure shows the nominal annual value of invoice assignments (SII, 2005–2025). Amounts in USD.

Table E.1: **Applicants are mostly micro and small firms**

	Full applicant data	Eligible applicants	Established billers
Number of suppliers	27,288	25,468	12,748
Micro and small firms (%)	62.5	62.2	71.3
Unknown firm size (%)	27.3	27.5	19.2
Median firm age (years)	2.5	2.5	3.1
Median annual billing (USD)	102,100	102,100	137,700
Median number of buyers	10	10	13
Median largest-customer share (%)	47.0	47.1	43.4

Notes: We give each supplier equal weight. Medians use available observations; billing and customer measures use the twelve complete months before application and require a year of history. Appendix E reports sample definitions, valid counts, and detailed distributions. Amounts in USD; we round billing to the nearest USD 100.

Figure E.2: **Most sales are to larger buyers**

Supplier size	Buyer size				No Sales	Unknown	Total
	Micro	Small	Medium	Large			
Micro	8.2%	16.7%	13.0%	46.1%	7.8%	8.3%	100%
Small	5.8%	12.5%	12.5%	54.4%	8.8%	6.0%	100%
Medium	4.6%	9.8%	9.6%	63.7%	6.4%	6.0%	100%
Large	5.2%	8.3%	9.5%	63.7%	9.8%	3.5%	100%
No Sales	10.3%	14.7%	12.3%	47.0%	6.6%	9.1%	100%
Unknown	6.8%	11.8%	9.6%	37.2%	27.2%	7.4%	100%

Rows sum to 100% before rounding. Darker cells show larger shares.

Notes: Rows report each supplier-size group's share of invoice value by buyer size. We use 9,555,314 positive-value invoices through March 30, 2026. We assign SII sales size from year $t - 2$ for January–August invoices and $t - 1$ otherwise, using the other year when the preferred year lacks a classification. Size measures sales, not creditworthiness.

Table E.2: Applicant Sample Coverage and Supplier Characteristics

	Full applicant data	Eligible applicants	Established billers
<i>A. Full invoice histories</i>			
Supplier firms	27,288	25,468	12,748
Buyer firms	583,966	543,152	462,039
Buyer–supplier pairs	1,361,919	1,247,865	957,726
Invoices	9,555,428	8,823,841	7,082,155
Active supplier-months	610,351	569,376	394,573
Invoice issue years	2003–2026	2003–2026	2008–2026
Total invoice value (USD billion)	22.6	21.4	17.3
<i>B. Supplier characteristics</i>			
Construction (%)	25.4	25.6	24.1
Wholesale and retail trade (%)	22.6	22.6	23.4
Agriculture, forestry, and fishing (%)	15.4	15.6	17.0
Professional and technical services (%)	10.2	10.3	8.9
Transport and communications (%)	9.7	9.8	11.2
Other sectors or unknown (%)	16.7	16.0	15.3
<i>Total across sectors (%)</i>	<i>100.0</i>	<i>100.0</i>	<i>100.0</i>
Micro (%)	40.5	40.6	43.4
Small (%)	22.0	21.5	27.9
Medium (%)	3.3	3.3	4.1
Large (%)	0.9	0.9	1.1
No Sales (%)	6.1	6.2	4.3
Unknown size (%)	27.3	27.5	19.2
<i>Total across sizes (%)</i>	<i>100.0</i>	<i>100.0</i>	<i>100.0</i>
Age (years), mean (median)	3.9 (2.5)	3.8 (2.5)	4.4 (3.1)
Firms with valid age	25,531	23,877	11,929
Firms with a year of prior history	11,723	11,423	8,829
Annual billing (USD thousand)	518.8 (102.1)	523.3 (102.1)	647.2 (137.7)
Buyers per supplier	35.3 (10.0)	35.0 (10.0)	42.2 (13.0)
Largest customer’s sales share (%)	51.1 (47.0)	51.1 (47.1)	47.9 (43.4)

Notes: Panel A uses each population’s full observed invoice history; active supplier-months require at least one invoice. The source contains 180 invoices from before 2017 (less than 0.002% of count and value), which we retain to reconcile the published source count. Eligible applicants form the common first-stage sample; established billers have at least USD 200 in sales in each of event months -2 , -1 , and 0 . Panel B gives suppliers equal weight. Sector and size shares sum to 100% before rounding. Annual billing and customer measures use the twelve complete calendar months before the reference application and require history reaching the beginning of that window. Continuous rows report means and medians in parentheses. Customer concentration requires positive billing, leaving 11,604, 11,314, and 8,829 suppliers in the respective columns. SII sizes use historical sales years under the rule in Figure E.2. Sectors come from the company-file snapshot. We use Section 3’s reference application when available and otherwise the first recorded application. Amounts in USD.

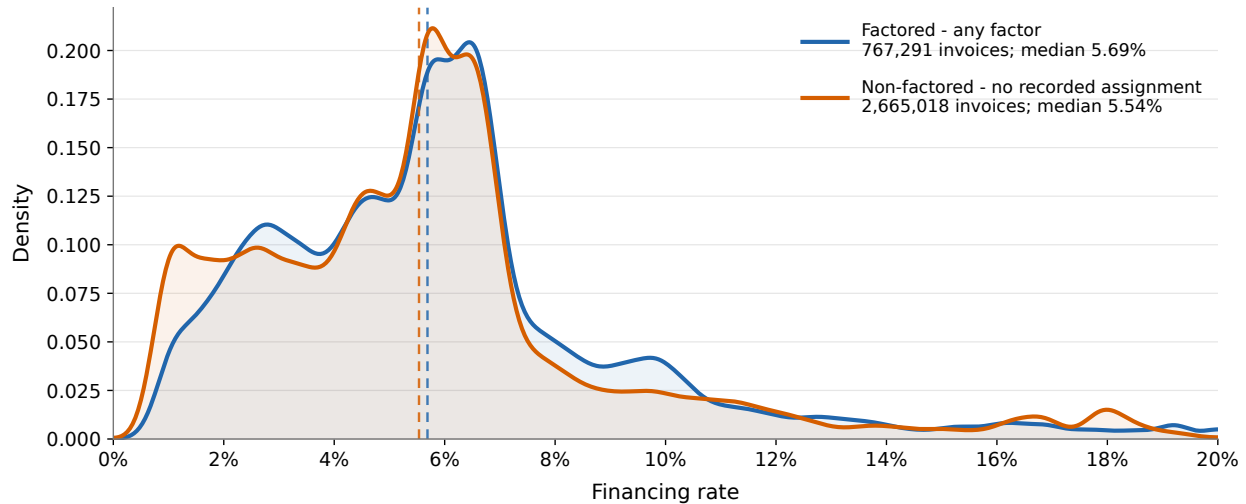
Table E.3: Coverage of applicant statistics by supplier size

	Suppliers	Invoices	Customer-share N	Size coverage (%)
All	11,723	2,440,604	11,604	78.2
Micro	5,515	452,444	5,462	48.0
Small	3,749	960,374	3,728	88.6
Medium	555	493,266	547	88.7
Large	138	371,078	134	91.3
No Sales	285	19,284	273	0.0
Unknown	1,481	144,158	1,460	0.0

	Median		Assignment share (%)	
	Annual sales (USD)	Largest customer (%)	Suppliers	Invoice value
No Sales	49,400	62.9	32.3	20.3
Unknown	62,000	54.9	40.0	20.4

Notes: This table documents Table 1. Supplier counts also give the denominators for annual-sales medians and assignment participation. Customer-share medians require positive sales. Size coverage equals the share of invoice value for which both counterparties have comparable positive-sales size categories. The larger-buyer share uses that invoice value as its denominator; no-sales and unknown groups have no size rank. We classify supplier and buyer size at the supplier's reference application: year $t - 2$ for January–August applications and $t - 1$ otherwise, using the other year when the preferred year lacks a classification. Historical SII categories can differ from sales in the baseline invoice window. We retain applicants whom X rejects and suppliers with no assignments. A recorded assignee identifies eventual assignment of a baseline invoice; it does not date financing relative to application. Amounts in USD; we round to the nearest USD 100.

Figure E.3: Own-financing rates by factoring status



Notes: We impute monthly own-financing rates for invoices across sectors from January 2019 through March 2026, starting one calendar month after each supplier's first X financing. We give each invoice equal weight; each curve integrates to one and dashed lines mark medians. Factored invoices have a recorded assignment to any factor; non-factored invoices have none. We use a Gaussian kernel with bandwidth 0.25 percentage points and reflect at 0% and 20%. Coverage exceeds 99.99% in both groups. Rates use only the common component for 26.5% of factored and 30.6% of non-factored invoices because supplier premiums lack support.

Table E.4: Buyer Characteristics and Credit-Grade Coverage

	Full applicant data	Eligible applicants	Established billers
<i>A. Supplier credit grades</i>			
Supplier firms	27,288	25,468	12,748
Firms with an A+–F credit grade	22,130	20,537	10,717
A+ or A among graded firms (%)	1.1	0.9	1.0
<i>B. Distinct buyers in the pre-application year</i>			
Buyer firms	279,931	271,876	250,964
Micro (%)	21.8	21.8	21.5
Small (%)	20.8	21.0	21.1
Medium (%)	6.3	6.4	6.6
Large (%)	4.0	4.0	4.3
No Sales (%)	5.4	5.3	5.3
Unknown size (%)	41.7	41.5	41.3
<i>Total across sizes (%)</i>	<i>100.0</i>	<i>100.0</i>	<i>100.0</i>
Buyers with an A+–F credit grade	30,046	28,807	26,853
A+ or A among graded buyers (%)	20.5	21.0	22.0

Notes: The columns follow the sample definitions in Table E.2. We give suppliers equal weight in Panel A and each distinct pre-application buyer equal weight in Panel B. Panel B uses the twelve complete calendar months before the reference application for suppliers with a year of prior history and measures buyer size at its first transaction in that window. SII sizes use historical sales years under the rule in Figure E.2; size shares sum to 100% before rounding. Credit grades come from the company-file snapshot; we do not treat grades as pre-application measures. The graded denominator excludes firms with a “new” or missing rating. Factor X’s grades cover 10.7% of distinct prior-year buyers in the full applicant data, so credit statistics describe a selected subset of customers.

Table E.5: Invoice Terms, Factoring Use, and Financing Costs

	Valid N	Mean / share	Median	P10	P90
<i>A. Invoice amounts and payment terms</i>					
Invoice face value (USD)	9,555,314	2,370	276	28	3,910
Invoice / annual billing (%)	2,440,604	0.475	0.036	0.001	1.007
Recorded payment term (days)	9,550,740	30.0	30.0	30.0	30.0
Issue to payment, X documents (days)	303,252	39.8	33.0	18.0	65.0
Late among observed X payments (%)	303,074	46.7	—	—	—
Contested invoices (%)	7,331,420	0.6	—	—	—
<i>B. Assignments of prior-year invoices and initial access to X</i>					
Suppliers with any assignment (%)	11,723	44.5	—	—	—
Assigned share of invoice count (%)	2,440,604	11.2	—	—	—
Assigned share of invoice value (%)	2,440,604	22.9	—	—	—
Invoice value assigned to X (%)	2,440,604	0.1	—	—	—
Invoice value to other assignees (%)	2,440,604	22.8	—	—	—
Initial request / annual billing, established firms (%)	8,829	10.1	4.1	0.8	17.4
Initial approval by decision count (%)	59,542	45.8	—	—	—
Initial approval by invoice value (%)	59,542	25.0	—	—	—
X operation among approved requests (%)	27,279	39.1	—	—	—
<i>C. Observed offers that became X operations</i>					
All-in term cost (%)	193,226	6.48	6.20	2.86	10.06
30-day simple-equivalent cost (%)	193,226	6.35	5.62	2.59	10.21
Interest over financing horizon (%)	193,226	2.33	2.20	1.27	3.36
Commission / advance (%)	193,226	4.15	3.73	0.83	7.55
Financing horizon (days)	193,226	33.8	31.0	24.0	51.0

Notes: Panel A uses positive-value invoices for amounts and nonnegative issue-to-due-date gaps for terms; the invoice/annual-billing ratio uses invoices in the pre-application year of firms with a year of prior history. Payment rows use 332,471 X-operated documents; 29,176 lack settlement dates and 43 have negative issue-to-payment intervals, which we exclude. We condition late-payment shares on valid settlement and due dates; missing settlement dates never count as on-time payments. The contested share uses invoices with a recorded nonmissing SII event classification. Panel B's first rows use invoices from the twelve complete pre-application months and the same history restriction. The assignment field records eventual cession; it does not date financing relative to application. The assignee tax identifier identifies X and other assignees; invalid identifiers remain unclassified. Initial requests use approval/rejection decisions in the first fourteen hours; pending requests do not enter this denominator. Repeated presentations remain separate decisions. The request/billing ratio uses established billers with a year of prior history. Operation dates identify realized financing. For value-weighted shares, N counts underlying invoices or decisions and the denominator is their summed face value. Panel C uses 193,226 approved, operated offers from 5,771 suppliers, with issue dates from 2019-01-01 to 2026-03-30. We require invoice issue dates from 2019 onward and at least one calendar month after the supplier's first observed X operation. Interest and commission use the same advance denominator; interest scales with the inclusive request-to-due-date horizon. The 30-day equivalent equals term cost times 30/ T . We retain positive term costs no greater than 20 percent under the existing measurement screen. These are observed offer terms conditional on operation, not imputed prices or rates at other factors. Amounts in USD; dashes denote inapplicable distributional statistics.

Table E.6: Own-financing benchmark: coverage and distribution by supplier size

Supplier size	Supplier-months	Suppliers	P25	Median	P75
Micro	23,732	3,381	3.28	5.17	7.85
Small	13,934	1,808	2.74	4.16	6.52
Medium	426	87	2.61	4.07	6.57
Large	36	11	1.61	2.83	3.15
No Sales	1,099	294	2.87	4.59	7.04
Unknown	7,592	1,392	3.56	5.50	7.97

Notes: This table documents Figure 1. We express rates as monthly percentages. We approximate suppliers’ loan rates with an own-financing benchmark. We construct this benchmark from a monthly common component and a fixed supplier premium, using accepted, operated financing offers. The sample covers 46,819 supplier-months for 5,771 suppliers from January 2019 through March 2026. We give each supplier-month equal weight and evaluate its rate at the last observed offer’s invoice issue date. We exclude nine supplier-months with fewer than five other donor suppliers; supplier premiums can use later evidence. We assign size from lagged SII sales, following the rule in Figure E.2. Firm counts overlap across size groups when firms change category. Unknown and no-sales classifications have no size rank. These proxies do not measure observed bank borrowing rates.

F Counterfactual accounting and supporting evidence

F.1 Accounting and aggregation

All results in this appendix use the same estimated economy as the main text: 26 buyers, 304 buyer–supplier relationships, 29,706 observed awards, and 255 suppliers. The sample contains USD 72,961,184.56 in total billing and USD 28,360,645.07 in total volume factored. We retain every supplier, including those whose profits fall, and evaluate the selected equilibrium on a 128×640 grid.

Aggregation and reporting units. We multiply each buyer’s expected welfare change per transaction opportunity by its observed total billing divided by expected payments per opportunity in the reference factoring equilibrium. We hold these weights fixed across regimes, sum across buyers, and express the result as a percentage of the total volume factored in the sample. The welfare change includes all modeled transactions, including those that suppliers finance with bank loans. We retain the original 64×320 billing calibration when we refine the forward grid. Each parameter draw uses its own saved original calibration, which we hold common across that draw’s financing regimes and grid comparisons.

Recipient accounting. We construct the recipient breakdowns in Figure 7(b)–(c) from the complete changes in equilibrium payoffs within each project category. For projects that proceed only with factoring, we record each party’s surplus in that equilibrium, since no party receives surplus without trade. For projects that change suppliers, we compare buyer surplus, the winning supplier’s profit after financing, and financial firms’ receipts across

the two equilibria. These comparisons incorporate changes in prices and interest payments. Summing across the three sectors cancels those payments and leaves the change in buyer value net of material production costs.

Table F.1 reports the complete accounting. The price and interest transfer columns cover only projects where the same supplier wins in both equilibria. The reallocation and expansion columns include each sector’s full payoff change within those categories. Under the main text’s assumption of no marginal financial resource costs, financing receipts equal financial-sector surplus. We do not add default transfers or impose a zero-profit condition on financial firms.

Table F.1: Welfare changes by recipient and mechanism

Recipient	Price transfers	Interest transfers	Reallocation	Output expansion	Total
Buyers	0.709836	0.000000	0.028319	0.004187	0.742342
Suppliers	−0.709836	2.121705	−0.085122	0.013861	1.340608
Financial sector	0.000000	−2.121705	0.028171	0.049678	−2.043855
All sectors	0.000000	0.000000	−0.028632	0.067727	0.039095

Notes: Entries express changes from the loan-only equilibrium to the factoring equilibrium as percentages of total volume factored. Price and interest transfers sum to zero across sectors. Each recipient’s four contributions sum to its total; totals use unrounded values.

Supplier profit accounting. Figure 8(a)–(b) separates supplier profit changes into financing, project volume, and margins before financing. For each buyer–supplier pair, let q denote the probability of winning, p the expected price conditional on winning, c the expected material cost conditional on winning, and r the financing rate over the invoice payment term. Define the margin before financing as $a = p - c$ and profit after financing per project as $m = p - c - rp$. Expected profit per opportunity equals $\Pi = qm$. With $\Delta x = x^1 - x^0$ and $\bar{x} = (x^1 + x^0)/2$, the symmetric product identity gives

$$\Delta \Pi = \underbrace{\bar{m} \Delta q}_{\text{project volume}} + \underbrace{\bar{q}(1 - \bar{r}) \Delta a}_{\text{margin before financing}} - \underbrace{\bar{q} \bar{r} \Delta c - \bar{q} \bar{p} \Delta r}_{\text{financing}}.$$

We calculate these contributions within pairs, apply the same buyer weights, and sum monetary amounts before dividing by each group’s total loan-only profits. The financing bar combines the rate contribution and the financing effect of changes in conditional production costs. It differs from the change in total interest spending, which also reflects changes in

invoice values and project volume. Changes in conditional margins can reflect both pricing responses and changes in the mix of projects a supplier wins; a negative margin contribution need not imply a decline in the group’s pooled average margin.

F.2 Distributional evidence

Supplier gains and losses. Factoring raises aggregate supplier profits while reducing profits for 131 of the 255 suppliers (51.4%). Another five suppliers have profit changes within USD 0.001 of zero, and 119 gain more than that amount. Figure 8(a) combines the 131 losers and five essentially unchanged suppliers; panel (b) contains the 119 winners. These groups use profit outcomes, not a cutoff in financing-rate relief. The first group loses USD 61,800.03 and the second gains USD 408,809.85, leaving an aggregate gain of USD 347,009.82, or 1.2236% of total volume factored.

Table F.2 gives the contributions behind the two waterfalls. Each row uses that group’s total profits without factoring as its denominator, so the group percentages do not add to the aggregate gain. Across all suppliers, baseline profits total USD 21,423,766.61. The same USD 347,009.82 gain therefore equals 1.6197% of baseline supplier profits and 1.2236% of total volume factored.

Table F.2: Supplier profit contributions by profit outcome

Supplier group	Suppliers	Financing	Project volume	Margin before financing	Net profit change
No better off	136	0.1561	−0.6321	−0.2051	−0.6812
Higher profits	119	4.5236	1.6643	−2.8780	3.3098
All suppliers	255	2.6740	0.6918	−1.7461	1.6197

Notes: Contributions express percentages of each row’s total loan-only profits after financing. *No better off* includes changes within USD 0.001 of zero. The financing, project-volume, and margin contributions sum to the net profit change before rounding.

Financing relief. Suppliers receive uneven rate reductions, and the largest reductions reach groups with the largest profit gains. Table F.3 separately classifies the 94 suppliers with no rate reduction and divides the remaining suppliers into terciles of their positive reductions. The no-reduction group accounts for 36.9% of suppliers. We calculate each supplier’s rate reduction using fixed observed invoice-value weights; the tercile cutoffs equal 0.2870 and 1.5032 percentage points. These rates cover the invoice payment term. They are not annual rates.

Table F.3: Financing rates and supplier outcomes

Rate group	Suppliers	Loan-only (%)	Factoring (%)	Rate cut (pp)	Profit change (USD thousands)	Losing
No rate cut	94	3.526	3.526	0.000	−42.805	89
Low reduction	54	4.150	4.017	0.133	−7.548	35
Medium reduction	53	5.600	4.649	0.951	166.329	5
High reduction	54	6.588	3.621	2.967	264.230	0
All suppliers	255	4.852	4.011	0.841	380.205	129

Notes: Rate averages use fixed observed invoice-value weights. We keep ties together when forming terciles of positive rate reductions. Profit changes sum across each supplier’s buyers and include all awards. *Losing* counts changes below −USD 0.001. These rate groups differ from the profit-outcome groups in Figure 8(a)–(b).

Interest savings turn an aggregate decline in profits before financing into a positive change in profits after financing. Across all suppliers, revenue net of material costs falls by USD 199,445.47, while total interest spending falls by USD 579,650.50. Their difference yields the USD 380,205.03 supplier gain. Before financing, 249 suppliers lose profits; after financing, 129 lose. These interest savings cover all awards and therefore differ from the 2.1217% continuing-winner interest transfer in Table F.1. All 26 buyers have nonnegative total surplus changes. This buyer result does not require every quote to fall: 195 relationships exhibit a higher conditional mean bid at some matched production costs.

Wedges and switching suppliers. The wedge statistics condition on transactions that proceed without factoring. For price p , material cost c , and financing rate r , define the markup $\mu = p - c/(1 - r)$ and financing wedge $f = rc/(1 - r)$, so $p - c = \mu + f$. These definitions distinguish the financing wedge from financial firms’ receipts rp and distinguish μ from the margin $p - c$ in the supplier-profit decomposition. Markups account for 90.7939% of the aggregate price–material-cost gap. We divide both wedges by buyer value, subtract their buyer-specific conditional means, and pool the weighted covariance and variances to obtain the within-buyer correlation of -0.557857 . This negative correlation concerns normalized wedges; their monetary levels have a positive within-buyer correlation.

On projects that change suppliers, new winners face average loan rates of 6.7278%, compared with 5.0740% for displaced suppliers, and receive average reductions of 2.2955 and 0.8508 percentage points, respectively. New winners create average buyer value of USD 4,287.08 at a material cost of USD 3,304.11; displaced suppliers create USD 3,116.85 at a cost of USD 2,102.89. The resulting surplus averages USD 982.97 and USD 1,013.95, respectively. These comparisons weight switching projects, rather than suppliers or relationships, and support the main text’s 3.1% average surplus difference on those projects.

Distribution of reallocation effects. Figure 8(c) shows both welfare gains and losses among projects that change suppliers. We hold production-cost realizations fixed across regimes and use the same action and tie draws. Across 211,236 simulated switches, the fixed buyer weights imply a welfare loss on 49.1% of switching projects and a gain on 50.9%; the mean change equals –USD 30.99 per switching project. We exclude additional projects, unchanged winners, and no-purchase outcomes from this conditional distribution. The plot retains all switches, pools the tails beyond USD 2,000 in either direction, and uses USD 200 bins within that range. Its weighted Gaussian kernel uses the unbinned switches and a bandwidth of USD 113.17. The empirical gain and loss shares come from the switches themselves, not from areas under the smoothed curve.

F.3 Uncertainty and numerical sensitivity

Parameter uncertainty. We propagate uncertainty in the estimated parameters through 128 antithetically paired joint normal draws of log parameters, using the qualified 315×315 covariance. All 128 draws and all 3,328 buyer–draw evaluations pass the numerical checks. Table F.4 reports the resulting dispersion and nominal symmetric intervals around the selected-grid estimates. The total-welfare standard deviation equals 0.008825 percentage points of total volume factored, giving a nominal 95% interval of [0.021798, 0.056391]%. The empirical 2.5th and 97.5th percentiles of the draw outcomes equal [0.026205, 0.061370]%. These calculations condition on the sample, supplier classifications, financing rates, and retention decisions. They exclude uncertainty from classification, rate construction, sample selection, grid resolution, and smoothing choices.

Table F.4: Parameter uncertainty on the selected grid

Outcome	Point estimate	Parameter-draw SD	Nominal 95% interval	
			Lower	Upper
Output expansion	0.067727	0.002683	0.062467	0.072986
Reallocation	–0.028632	0.007780	–0.043879	–0.013384
Total welfare	0.039095	0.008825	0.021798	0.056391
Buyer surplus	0.742342	0.014414	0.714091	0.770593
Supplier profits	1.340608	0.033236	1.275467	1.405749
Financial-sector surplus	–2.043855	0.029811	–2.102284	–1.985426

Notes: All entries use percentages of total volume factored. Nominal intervals equal the point estimate plus or minus 1.96 times the parameter-draw standard deviation. The calculations use 128 complete joint draws and hold classifications and the sample fixed. Raw draw dispersion does not subtract simulation variance from simulated recipient-level mechanism cells.

Simulation error. Numerical integration variation measures a different source of uncertainty from variation in estimated parameters. Exact finite-grid endpoint calculations determine the sector totals, total expansion, and total reallocation in Table F.1. We use four rotated banks of 262,144 common Halton draws to allocate continuing-winner transfers and recipient-level reallocation at the point estimate. The buyer-reallocation integration standard error equals 0.000210 percentage points. Within each parameter draw, four banks of 16,384 draws yield a root-mean-square integration standard error of 0.001575, compared with raw propagated dispersion of 0.001805. We report these measures separately and do not subtract simulation variance from the propagated dispersion. Consequently, the latter does not isolate parameter uncertainty in that simulated cell.

The switching-project histogram also uses simulated transitions. Its positive and negative reallocation contributions equal 0.256927% and -0.283452% of total volume factored, giving a simulated net of -0.026525% with an integration standard error of 0.001607 percentage points. The main text uses the exact finite-grid net of -0.028632% . We retain this difference rather than rescale the histogram to match the endpoint calculation. The transition distribution depends on the common cost, action, and tie draws; the kernel describes that distribution and does not supply a confidence interval.

Grid and smoothing sensitivity. The full-equilibrium welfare gain remains positive across the numerical variants in Table F.5, but its magnitude changes. Refining the grid from 64×320 to 128×640 lowers the gain by 16.3%, from 0.046714% to 0.039095% of total volume factored. Halving the positive smoothing temperature raises the selected-grid gain by 43.2%, to 0.055973%. Tightening the response tolerance changes the total by less than 2×10^{-14} percentage points. These comparisons hold the estimated primitives and original billing calibrations fixed; only the stated numerical setting changes. They measure sensitivity outside the parameter intervals, and the smaller parameter-draw dispersion on the refined grid does not imply that grid refinement generally improves statistical precision.

Table F.5: Sensitivity to the numerical solution

Variant	Buyers	Suppliers	Finance	Total welfare
Selected reference	0.742342	1.340608	-2.043855	0.039095
Coarser grid (64×320)	0.716706	1.383431	-2.053424	0.046714
Half smoothing temperature	0.736947	1.417690	-2.098663	0.055973
Tighter response tolerance	0.742342	1.340608	-2.043855	0.039095

Notes: Entries express changes as percentages of total volume factored. All variants use the same estimates, sample, and original billing calibration. The cooler and tighter-tolerance variants use the 128×640 grid. Each row changes only the indicated setting.

Boundary refinement. An additional check of output expansion finds greater sensitivity in the allocation of surplus than in its total. The sum of absolute buyer-level changes in output buyer surplus between the fine and targeted boundary grids equals USD 65.03, exceeding the predeclared USD 5 threshold. We retain this failed check. The discrepancy equals 0.000229% of total volume factored and 0.0309% of the aggregate buyer gain. Total expansion welfare changes by only USD 0.37 between those two grids, but buyers' expansion surplus rises from 0.004187% on the selected uniform grid to 0.008875% on the fine boundary grid and 0.009104% on the targeted grid. This output-only comparison does not validate reallocation.

In a separate direct-effect exercise, we evaluate the loan-only pricing rules at financing-adjusted costs without recomputing those rules. This frozen-rule comparison changes sign across grids: total welfare equals -0.007235% on the selected grid and $+0.011999\%$ on the coarse grid. Thus, the numerical exercises do not establish a robust sign for that direct effect, even though all reported full-equilibrium variants deliver positive total gains. The results describe finite grids with positive smoothing; they do not establish the corresponding equilibrium with continuous actions and zero smoothing. Rate-path kernels and descriptive correlations do not establish that limit.