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Contingent Payments in Procurement Interactions - Experimental Evidence

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Comments

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Abstract

A chief objective of creating competition among suppliers is the procurement of higher quality goods at lower prices. When procuring non-standard goods, it is often difficult to write a complete specification of desired quality in the contract. A moral hazard arises when this quality is costly and determined by the supplier ex post to contracting. In an effort to mitigate this moral hazard, we introduce a correlated contingent payment contract. This contract is awarded through competitive bidding. The winning supplier's payment is, according to a fixed probability, either the amount of their bid or a quality contingent amount that depends on the bid and an exogenous norm for how a seller and buyer split social surplus. We show, both theoretically and experimentally, there is a "Goldilocks" region for high quality to emerge in which the probability of quality contingent payment is large enough to reward high quality provision, but not too large to induce overly aggressive bidding. This optimal implementation only relies upon preferences for maximizing one's own profit and the rationality of backward induction. A surprising experimental result is that suppliers earned positive economic profits within this region. We estimate a structural model of bounded rationality to show that risk aversion can explain this result. These results have managerial implications for the design of contingent payments in contracts.

Keywords: contingent payment, procurement, bidding, risk aversion, experiment
JEL codes: C70, C92, D86

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1 Introduction

A chief objective of creating competition among suppliers is the procurement of better goods and services at lower prices. However, competition is often conducted solely on price, and outside the case of commodities, leads to low cost and low quality goods.[1] When quality is costly and determined by the supplier ex post to contracting, the low cost-low quality outcome results from a moral hazard.

In the pharmaceutical industry one frequently finds low cost-low quality outcomes. Bate et al. (2011) examined a sample of essential medicines approved by the World Health Organization and 15% of this sample failed at least one quality test. Further, failing drugs were priced significantly lower than non-failing drugs. A reduction in quality among approved essential medicines offered at lower prices has important implications for procurement policy. For example, The Global Fund to Fight AIDS, Tuberculosis and Malaria is one of the largest procurers of health products for developing countries. Included in The Global Fund's procurement principles is a stated aim to achieve "the lowest possible price for products of assured quality" (Global Fund, 2021, p. 7). This focus on price-based selection has previously led to reported supply problems in Kenya and Uganda (Tren et al., 2009).

We introduce a correlated contingent payment contract (CCPC) that can mitigate supplier moral hazard ex post to contracting while retaining supplier selection ex ante based on price. The contract is allocated via a price-only auction and costly quality is determined by the supplier after the auction. The buyer prefers high to low quality and, while high quality costs more than low quality, it maximizes total surplus. However, the buyer cannot specify the quality level in the contract or verify quality ex post.

In practice, for example in the construction industry[2], arbitrators are frequently used

[1] Quality in our setting is defined broadly and may refer to outcomes such as delivery time, the quality of materials used or the health and safety of production processes.

[2] Until 2007, arbitration was the preferred dispute resolution method in United States construction contracts by default. Construction case filings at the American Arbitration Association continue to increase, up 6% in 2019, with complex new cases rising at twice this rate (see the Arbitration Association Annual Report at *adr.org/annual-reports*).

to verify the performance of contract parties and assess payoff implications. The CCPC is a stylized version of this resolution process which starts with an arbitrator who can only randomly verify quality according to a fixed probability. Then, contingent on verification, the arbitrator assigns final payments according to a pre-determined performance rule. This rule maps the supplier's quality decision into a final payment allocation that implements a preferred surplus division. This division rule allocates proportions of the total realized surplus to the buyer and supplier that are fixed across quality levels and reflects the importance of the supplier's profitability in the arbitrator's preferences.[3]

How does the shadow of contingent payments influence strategic behaviour during the supplier selection stage? In a CCPC, the range of quality contingent payments is proportional to the winning bid. This implies there is a limit to supplier gains through arbitration and this limit is lower if suppliers bid more aggressively. For example, most construction contracts use retention provisions, which is a fixed percentage of the contract value (usually 5-10%) withheld by the buyer until project completion (Bausman, 2004). A supplier who wins the contract with a lower bid and disputes the withholding of retention monies ex post may recover less in absolute terms but more in higher value contracts. The influence this payment flexibility is found in the observation that suppliers incorporate this expectation into their bidding strategies. Evidence that suppliers strategically backward induct can be found in industry reports.[4]

In this setting we show, both theoretically and experimentally, there is a "Goldilocks" region of probabilities that contingent payments are implemented in for which high quality is the unique equilibrium outcome. The probability of a contingent payment is large enough to reward high quality, but not so large as to induce overly aggressive bidding competition.[5]

[3] For a mechanism design approach to arbitration in procurement with cost contingencies and supplier moral hazard ex ante to contracting (rather than ex post), see Herweg and Schmidt (2020).

[4] The following quote from an international arbitration survey in the construction sector is a case in point: "Some interviewees noted that they had observed project participants bidding a lower price upon the expectation of recovering sums through variation orders which, if disputed, could be arbitrated" (Pinsent-Masons, 2019, p.7).

[5] Outside of a procurement setting, Gabuthy and Muthoo (2019) show an efficiency-enhancing effect of contingent payments arising from arbitration in employment relationships.

Thus, an over-reliance on contingent payments in the contract may undermine supplier performance. The effectiveness of the CCPC in promoting high quality relies (only) upon each party seeking to maximize his own expected profit.

Why not write a complete contract? In procurement, the awarding of the contract is only the beginning of the relationship between the buyer and the winning supplier. Contingencies may arise during the trading relationship that are unforeseen, costly to contract upon, or difficult to verify (Tirole, 1999). Thus, it is often difficult to write a complete specification of desired quality in the contract ex ante. Selecting suppliers based on price then creates a tension between competition and cooperation. This tension has been documented in the construction industry. Bajari et al. (2009) report that competition based on price is less likely to be used for complex or non-standard projects in the private sector. However, in public procurement, principles of fair competition usually require selection based on a standard price-only auction, which can result in significant ex post supplier adjustments and cost overruns (Bajari et al., 2014).

In settings where price-only competition is not mandated, alternative mechanisms may be used to mitigate the supplier moral hazard problem. Earlier theoretical and experimental work focused on procurement auction design for differentiated products with exogenous non-price supplier attributes. These studies assume that the winning supplier receives a fixed price equal to the winning (or next best) bid and that it is neither feasible nor profitable for the supplier to modify quality after allocation of the contract.[6] Recent studies have considered buyer-determined auctions, (Brosig-Koch and Heinrich, 2014, 2018; Fugger et al., 2019) and discretionary bonus incentives (Walker et al., 2022). However, moving away from a binding commitment to procure at the lowest price is not always palatable from a regulatory perspective as it may promote collusion (Fugger et al., 2016) or discrimination in the contract award process (Verdeaux, 2003). Buyer-determined mechanisms also rely upon repeated

[6]Engelbrecht-Wiggans et al. (2007) derive conditions under which a commitment to procure at the lowest price is optimal. Kostamis et al. (2009) compare the relative efficiency of open-bid and sealed-bid auctions. Shachat and Swarthout (2010) test the performance of a modified English auction in which potential suppliers receive bidding credits based on previously observed quality differences.

game or social utility arguments to implement high quality. These mechanisms cannot necessarily be relied upon in procurement interactions and depend for their effectiveness on the system of beliefs among market participants. In contrast, the CCPC does not rely upon contract parties having positive regard for the material welfare of the other parties. This gives us more confidence in the external validity and value in practice of our results.

We design an experiment to empirically test the effectiveness of the CCPC in mitigating supplier moral hazard. Specifically, we compare the performance of three treatments. The baseline treatment is a voluntary post delivery payment contract in which the probability of receiving a contingent payment is zero. In this treatment, any payment for quality delivered that is in addition to the supplier's bid is at the discretion of the buyer. We then consider two variants of the CCPC, which differ according to whether the probability of receiving a contingent payment is set inside or above the "Goldilocks" region for high quality. This is the only parameter that differs among the three treatments.

The experimental findings confirm that bids are decreasing in the probability of receiving a contingent payment. The data also support the prediction that, for high quality to emerge as a stable procurement outcome over time, the contract must avoid too much likelihood of contingent payments. Thus, we provide qualitative insights for procurement managers on how to design contingent payments in competitively allocated contracts to promote consummate contractual performance.[7]

A key experimental result not predicted by the theory is that suppliers earn significantly greater profits inside the "Goldilocks" region than outside of it.[8] To explain this result, we identify three plausible behavioural mechanisms which are important factors influencing

[7] The importance of responsible contract behaviour has gained renewed attention in the wake of the COVID-19 pandemic. In 2020, the British government released specific guidance on this issue: "Responsible and fair behaviour in contracts now – in particular in dealing with potential disputes – will result in better long-term outcomes for jobs and our economy" (Cabinet-Office, 2020).

[8] In a wide variety of settings in which there is market competition with symmetric and an excess number of suppliers theoretical work predicts, which experimental studies robustly confirm, suppliers earn zero economic profits. These settings include market entry games (Sundali et al., 1995; Rapoport et al., 1998), auctions with entry costs (Levin and Smith, 1994), and competitive markets in the long-run (Shachat and Zhang, 2017).

buyer-supplier relations in procurement projects: bounded rationality, risk aversion and trust. We estimate a structural model that nests these three behavioural factors. The behavioural model estimation yields two insights. First, risk aversion can drive bids above the equilibrium level in anticipation of an uncertain contingent payment and generate positive supplier rents. Second, the expectation of receiving a contingent payment may substitute for trust in the buyer-supplier relationship. The latter finding is reinforced by the results of a follow-up experiment with no buyer role, which enables us to control for suppliers' expectations of reciprocity.

In addition to the procurement auction literature discussed above, we contribute to the integration of academic literature on incomplete contracting and the auctioning of incentive contracts. At least two previous experimental studies auction off incentive contracts in which payments are tied to outcomes under conditions of supplier-side moral hazard. Cox et al. (1996) show that conditioning payments on cost realizations worsens the supplier-side moral hazard problem. Onderstal and Van de Meerendonk (2009) find experimentally that price-only and scoring auctions are efficient with optimal contingent payments. Unlike these studies, we drop the assumption that outcomes are perfectly contractible ex ante.

Finally, we contribute to operations literature documenting that behavioural factors may influence the effectiveness of incentive contracts (see, e.g., Davis and Hyndman, 2018; Li et al., 2020). We estimate a novel application of a quantal response equilibrium model to generate new insights on how the anticipation of contingent monetary incentives influences strategic behaviour and other-regarding preferences in a competitive bidding environment.

The paper proceeds as follows. In Section 2, we present a simple procurement model to capture the trade-offs of interest and introduce the CCPC. In Section 3, we describe the experiment and hypotheses. In Section 4, we summarize the experimental results. In Section 5, we estimate our behavioural model. In Section 6, we conclude the paper with a discussion of managerial insights and limitations of the model and experiment.

2 Analysis of Contracts

We first outline the contracting environment. A single buyer seeks to procure one unit of an indivisible good or service from a pool of $n \geq 2$ pre-qualified suppliers, indexed by i. We assume that these suppliers are homogeneous ex ante. This ensures that we capture differences in actual quality delivered ex post.

At Date 0, the suppliers compete on price to deliver the contract. Each supplier submits a sealed bid b_i at a first-price reverse auction, with a commitment to procure at the lowest price. The selected supplier is the one submitting the lowest priced bid b (hereafter, the seller). If two or more suppliers submit the same bid, the tie is broken randomly. Any non-selected supplier is no longer considered in the interaction and earns an outside option w_S. For the purpose of exposition in this section only, we set $w_S = 0$.

In a departure from the standard auction setup, the winning bid determines a feasible contract price range, $[X, Y]$, rather than a single fixed price. Without loss of generality, we set the lower bound contract price at $X = b$. We define $Y = \alpha b$, with $\alpha \geq 1$, to be a linear function that maps the winning bid to an upper bound contract price. The parameter α defines the level of price flexibility. The reason for setting an upper bound is to restrict the maximum payment that can be recovered by any supplier such that it is positively related to the bid. The linear specification permits more price flexibility in higher value contracts. For example, as described in the introduction, most construction contracts use retention provisions, which is a fixed percentage of the contract value. Thus, the bid level directly influences the maximum amount that can be recovered by the seller. A fixed-price contract is captured in our model as the special case $\alpha = 1$.

At Date 1, a bilateral trade relationship forms between the buyer and seller, and the seller determines the quality of the contract. We discretize the action space such that the seller delivers either low quality ($q = q^L$) or high quality ($q = q^H$). This restricts attention to performance at the extensive margin. The seller's quality choice q maps directly to his own unit cost $c(q)$, and the buyer's unit valuation $v(q)$. The seller's cost of delivering high

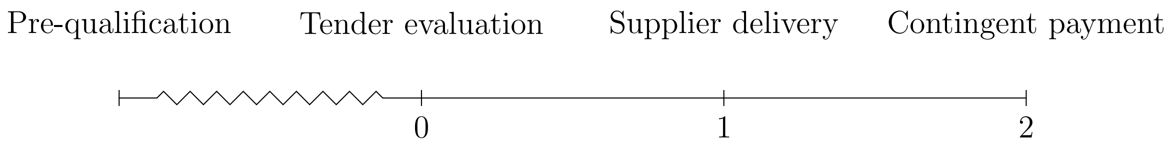

Figure 1: Dates in the model.

quality is strictly greater than for low quality, i.e., $c(q^H) > c(q^L)$, and high quality is the efficient outcome, i.e., $v(q^H) - c(q^H) > v(q^L) - c(q^L) > 0$. These parameters ensure that the total surplus generated is solely determined by the seller's chosen quality and that high quality maximizes total surplus.

At Date 2, the final payment for quality provided is determined, constrained to fall within the terms of the Date 0 contract, and paid out from the buyer to seller, $p \in [b, \alpha b]$. How this payment is determined will be described below.

The timeline of events is summarised in Figure 1. The payoffs of the buyer and seller are as follows:

$$\begin{aligned} \pi_B &= v(q) - p. \\ \pi_S &= p - c(q). \end{aligned} \tag{1}$$

We assume that the buyer cannot specify the quality level in the contract. However, a third-party arbitrator (outside of the model) can verify the quality delivered by the supplier at Date 1 with probability σ. If quality cannot be verified, then any payment at Date 2 in addition to the supplier's bid is at the discretion of the buyer. Contingent on quality verification, the arbitrator assigns final payments at Date 2 according to a pre-determined performance rule:

$$z(q) = \mu v(q) + (1 - \mu)c(q) \tag{2}$$

where $0 < \mu < 1$ is a commonly known and exogenous parameter representing the share of the total surplus created which is due to the seller.[9] This parameter represents the weight given to the supplier in the arbitrator's preferences. We do not advocate as to the underlying

[9] The process that determines μ is beyond the scope of the model.

driver of this preference. One possibility is a fairness norm, which is specific to the industry or locale. If the bid is such that $z(q)$ is not in the feasible contract price range determined in the Date 0 auction, then the arbitrator minimizes the distance between the assigned payment and the performance rule. Specifically, if the seller bid very low in the auction such that the bid, b, is below $z(q)/\alpha$, then the arbitrator would award the seller an amount equal to αb. Similarly, if the seller bid very high in the auction such that the bid, b, is above $z(q)$, then the arbitrator would award the seller an amount equal to b.

It is straightforward to verify that the performance rule in (2) satisfies the following:[10]

(i) $c(q) < z(q) < v(q)$ for $q \in \{q^L, q^H\}$; and

(ii) $z(q^L)(c(q^H) - c(q^L)) < c(q^L)(z(q^H) - z(q^L))$.

Thus, the quality-contingent payment covers the seller's opportunity cost of submitting a bid; and conditional on bidding above the cost of high quality (not assumed), high quality is incentive compatible in the perfectly correlated contingent contract (i.e., when $\sigma = 1$).

In summary, the correlated contingent payment contract can be written as follows:

$$p = \begin{cases} p_A, & \text{with probability } \sigma; \\ b + p_B, & \text{with probability } (1-\sigma). \end{cases} \tag{3}$$

where $p_A = max\{b, min\{z(q), \alpha b\}\}$ and $p_B \in [0, (\alpha - 1)b]$. Equation (3) is similar in nature to a cash bid plus fixed contract (see Skrzypacz, 2013).

Formally, a supplier i's strategy has two components: a bid $b_i \geq c(q^L)/\alpha$ and a quality choice function $q_i(b_i) \in \{q^L, q^H\}$. The minimum bid precludes dominated strategies. We assume throughout this section that the buyer acts to maximize own expected profit and so $p_B = 0$.[11] As the buyer's strategy is determined ex post by the outcome of the contract

[10] The propositions outlined below do not rely on a linear functional form for the performance rule, so long as these two conditions are satisfied.

[11] In our analysis of the experiment data, we consider the possibility of performance-based reciprocity based on other-regarding preferences.

in (3), we exclude this strategy from the equilibria characterised below. The solution concept is subgame perfect Nash equilibrium (SPNE) in pure strategies. We are interested in whether there exists a procurement outcome in which high quality is an incentive compatible component of the potential suppliers' equilibrium bidding strategy. High quality is incentive compatible in our model if it is strictly preferred by the seller to both low quality and the outside option. The proofs are contained in Appendix A.1

2.1 Non-contingent contract

If quality cannot be verified, then we have a non-contingent contract.

Proposition 1. *If $\sigma = 0$, then high quality is not an equilibrium outcome.*

Proposition 1 captures the supplier-side moral hazard when a fixed-price contract is allocated at a price-only auction. The unique SPNE outcome of the non-contingent contract is $b_i^* = c(q^L)$ and $q_i^* = q^L$ for all i. This will serve as the benchmark against which we measure the efficiency of a contingent payment contract.

2.2 Correlated contingent payment contract (CCPC)

We now consider the possibility that quality can be verified ($\sigma > 0$). Based on (1) and (3), the expected payoffs to the buyer and seller are summarized as follows:

$$\begin{aligned} E[\pi_B] &= v(q) - (1-\sigma)b - \sigma p_A. \\ E[\pi_S] &= (1-\sigma)b + \sigma p_A - c(q). \end{aligned} \tag{4}$$

Clearly, a necessary condition for the CCPC to be effective is $\alpha > 1$. A sufficient condition is described in the following proposition.

Proposition 2. *If $\sigma \in (\psi^a, \psi^b)$ and $\alpha \geq \alpha_{min}(\sigma)$, where $\psi^a = \frac{c(q^H)-c(q^L)}{z(q^H)-z(q^L)}$, $\psi^b = \frac{c(q^L)}{z(q^L)}$ and $\alpha_{min}(\sigma) = 1 + \frac{c(q^H)-c(q^L)-\sigma(c(q^H)-z(q^L))}{\sigma(c(q^L)-\sigma z(q^L))}$, then high quality is the unique equilibrium outcome.*

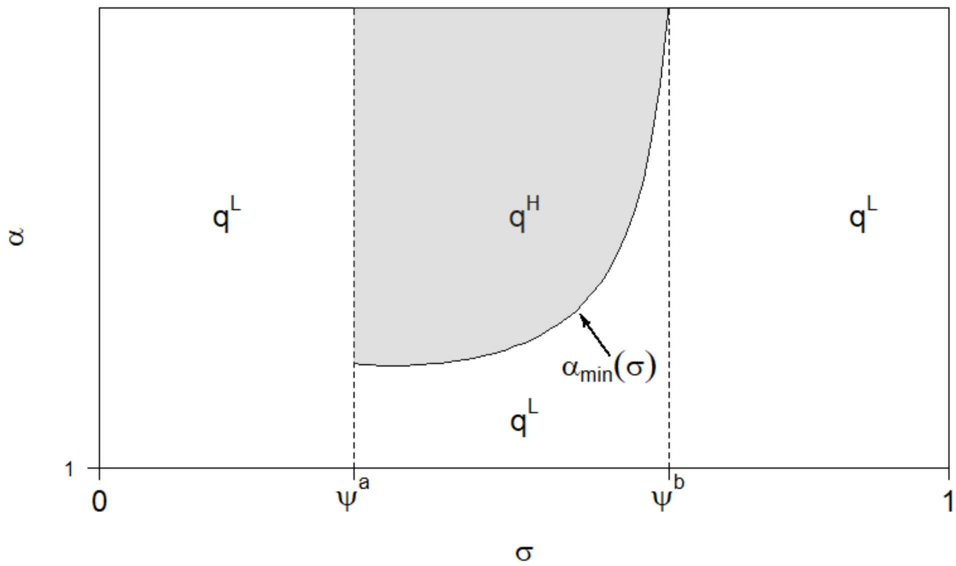

Figure 2: The "Goldilocks" region for high quality in the CCPC.

Notes. For contracts in the grey shaded region, high quality is the unique equilibrium outcome.

Proposition 2 implies that, for the CCPC to be effective, there is a "Goldilocks" region in which σ is large enough to incentivise high quality delivery, but not so large as to allow potential suppliers to reduce their bids too far in the Date 0 auction. The crux of the proof is to identify the parameter region for which the price at which suppliers are indifferent to winning the contract conditional on delivering high quality is strictly below the price at which suppliers are indifferent to winning the contract conditional on delivering low quality. That is, the break-even bid associated with high quality is lower than the break-even bid associated with low quality.

Then, due to the binding selection rule, the no-deviation incentives at any bid above the lower break-even bid are identical to Proposition 1: higher equilibrium bids are not possible because suppliers have an incentive to undercut, while lower bids are not profitable. Each SPNE outcome of the CCPC associated with high quality is characterised as follows: $b_i^* = max\{\frac{c(q^H)-\sigma z(q^H)}{(1-\sigma)}, \frac{c(q^H)}{1+(\alpha-1)\sigma}\}$ and $q_i^* = q^H$ for all i.

In Figure 2, we illustrate the "Goldilocks" region in (σ, α) space for parameter values that we will use in the experiment. The constraint on σ is independent of α and requires a minimum and a maximum contingent payment probability. The lower envelope of the region is defined by $\alpha_{min}(\sigma)$ and requires that the probability of receiving a contingent payment be higher in more flexible contracts.

The following corollaries follow directly from Propositions 1 and 2.

Corollary 1. *Equilibrium bids are decreasing in the probability of a contingent payment.*

This corollary can rationalise more aggressive bidding upon a greater expectation of recovering sums through arbitration.

Corollary 2. *Sellers' profits are more variable with contingent payments than without.*

Thus, we expect to see both positive and negative profits in the market, depending on the realization of the contingent payment.

3 Experimental Design and Hypotheses

3.1 Experimental design

To test the effectiveness of the correlated contingent payment contract in mitigating supplier moral hazard, we evaluate three procurement contracts in the lab, each in a separate between-subjects experimental treatment (Table 1). We use $\alpha = 4$ for all three contracts.

In the *Baseline* treatment, we test the non-contingent contract, and so the probability of receiving a contingent payment is $\sigma = 0$.

In the other two treatments, we introduce contingent payments and vary $\sigma > 0$. We use an independent arbitrator (outside the experiment) as a device to describe the contingency to subjects: the probability of receiving a contingent payment is the probability with which the arbitrator is available to determine final payment. Specifically, this probability is set at $\sigma = 3/6$ in the *Arbitrator-36* treatment and $\sigma = 5/6$ in the *Arbitrator-56* treatment. The

Treatment	*Baseline*	*Arbitrator-36*	*Arbitrator-56*
Contingent payment probability	$\sigma = 0/6$	$\sigma = 3/6$	$\sigma = 5/6$

Constant parameters: $\alpha = 4, \mu = 0.6, w_S = 5, c(q^L) = 30, c(q^H) = 40, v(q^L) = 50$ and $v(q^H) = 100$.

Table 1: Treatments and parameters.

probabilistic nature of the Arbitrator was explained to subjects using a standard six-sided die (hence the treatment names). The performance rule is defined by equation (2), with $\mu = 0.6$; we deliberately avoid invoking norms associated with an equal surplus split (see, e.g., Andreoni and Bernheim, 2009). As the market imbalance favours the buyer, we chose an arbitrator that prefers to award the seller a majority share of the trading surplus.

3.2 Procedure

The experimental protocol proceeds as follows. We recruit 18 subjects to participate in a 60-minute session. We randomly assign 6 subjects to the role of a buyer and 12 subjects to the role of a supplier. Roles remain fixed. Each session consists of 2 practice periods and 35 rounds. Thus, we have data from 6 groups per round. At the beginning of each round, we randomly match subjects into groups of three (one buyer and two suppliers). An algorithm ensured that no subject played with the same two participants in consecutive rounds. Subjects are informed about the matching protocol, cost and valuation schedules. We refer to "low quality" as "normal quality" in the experiment to avoid using a term that might have negative connotations unrelated to the monetary incentive. We will continue to use the first term here.

Low quality generates a trading surplus of 20 and high quality generates a surplus of 60. Low quality costs the supplier 30 to deliver and is valued by the buyer at 50. High quality costs the supplier 40 to deliver and is valued by the buyer at 100. Consistent with the investment game in experimental economics (Berg et al., 1995), the surplus multiplier is three. For any non-selected supplier, the outside option is $w_S = 5$ and the discreteness of the grid is $\Delta = 0.25$. The minimum bid is 9 (to preclude dominated supplier strategies) and the maximum bid is 50. The maximum bid is high enough to ensure that suppliers can submit a profitable bid associated with either low or high quality, and low enough to preclude a bid that would force the buyer into making a loss. Suppliers submit price and quality choices conditional on winning the contract. [12] Upon notification of the price and quality, the buyer has an opportunity to send an additional payment to the supplier. If the Arbitrator acts, then contingent payments are implemented.

We conducted 8 sessions per treatment at the laboratory of the Center for Behavioral and Experimental Research at Wuhan University and in accordance with its ethics protocols. The final sample size is 432 subjects (144 buyers and 288 suppliers) each with 35 observations. This yields a total of 10,080 bidding strategies and 5,040 procurement contracts for analysis. Participants were students (Chinese nationals) registered on a wide range of academic majors at Wuhan University, recruited and paid using the Ancademy platform (ancademy.org). The mean age in our sample is 20.5 and 56% of subjects are female. Average earnings were 48.17 RMB, including a show-up fee of 15 RMB. The translated instructions are available in a supplementary document. At the end of a session, subjects completed a short post-experiment survey, which included questions about their age, gender and income. We also elicited self-reported measures of trust and risk preferences (Dohmen et al., 2011). The experimental software was programmed in oTree (Chen et al., 2016). Further details about the procedure and sample characteristics are provided in Appendix A.5.

3.3 Hypotheses

We chose the contract parameters such that high quality is the unique equilibrium outcome in the *Arbitrator-36* treatment, and low quality is the unique equilibrium outcome in the *Baseline* and *Arbitrator-56* treatments. Thus, we can test our prediction that the probability of receiving a contingent payment must be large enough to reward high quality, but not so

[12] This strategy method for supplier subjects enables us to collect twice as many quality observations without changing the strategic nature of the game. Further additional benefits are strengthened anonymity of the seller and shorter wait times in the experiment.

Treatment	*Baseline*	*Arbitrator-36*	*Arbitrator-56*
Bid	35	18	10
Quality	Low	High	Low
Buyer's profit	15	55	15
Seller's profit	5	5	5

Table 2: Equilibrium predictions in the experiment.

large as to induce overly aggressive bidding competition in the auction.

In Table 2, we present the equilibrium predictions for bids and quality choices in each treatment. Given our experiment parameters, the equilibrium bid is 35 in *Baseline*, 18 in *Arbitrator-36* and 10 in *Arbitrator-56*. Buyers are predicted to appropriate the full trading surplus in excess of the seller's outside option in all treatments. However, in *Arbitrator-36* and *Arbitrator-56*, this prediction is in expectation only. Thus, empirically, if suppliers are risk-averse then we might observe a risk premium in bids, a possibility that we will consider formally in Section 5. The main hypotheses to be tested are summarised as follows:

Hypothesis 1. *Winning bids are rank ordered as Baseline > Arbitrator-36 > Arbitrator-56.*

Hypothesis 2. *High quality is more likely in Arbitrator-36 than Baseline or Arbitrator-56.*

Hypothesis 3. *The buyer's profit is higher in Arbitrator-36 than Baseline or Arbitrator-56; the seller earns zero economic profit on average in each treatment, but this is more variable in Arbitrator-36 than Baseline or Arbitrator-56.*

3.4 Robustness check: Follow-up experiment with no buyer role

In a follow-up experiment, we conducted the main arbitrator treatments with no subject in a buyer role (we will refer to these follow-up treatments as *Arbitrator-36N* and *Arbitrator-56N*, respectively). This precludes the possibility of reciprocity in transactions and can also mitigate artefactual social preferences between supplier and buyer participants. Therefore, we can check whether beliefs about reciprocity are influencing bidding behaviour. In this variant, the supplier who wins the auction either receives the arbitrator's price with probability σ, or the bid with probability $(1 - \sigma)$. Except for this change, we used the same protocol and instructions as for the main treatments. We recruited 192 new subjects for the follow-up experiment across 8 independent cohorts of 6 groups (12 suppliers) per treatment (average earnings of 46.72 RMB). The predictions for these treatments are unchanged from Table 2.

4 Experimental Results

This section outlines the main experimental results. In Section 4.1, we present summary statistics from the procurement interactions and test our hypotheses at the aggregate level in relation to the equilibrium predictions. In Section 4.2, we report the results of our follow-up experiment with no buyer as a robustness check.

4.1 Main treatment effects

The main findings are summarised in the first three columns of Table 3. Session averages are provided for winning bids, the frequency of high quality, the buyer's voluntary increment (defined as the buyer's price choice minus the winning bid), and the buyer and seller profits. To mitigate learning effects, we calculate these averages based on the last 20 rounds only. The results are qualitatively unchanged by using data from all 35 rounds.[13]

Bidding. Hypothesis 1 states that winning bids are increasing in the probability of receiving a contingent payment. The data supports this hypothesis. In *Baseline*, the average bid submitted is 37.78; in *Arbitrator-36*, 31.76; and in *Arbitrator-56*, 15.02. The average winning bids (the lower-order bidding statistic) are 36.57, 29.33 and 13.1, respectively. All six pairwise comparisons among the treatments are significant (p-values < 0.001).[14] Beyond the

[13]The results are robust to controlling for intra-session correlations using a regression analysis based on disaggregated data at the matching group level. We further analyze heterogeneity at the session level and find support for the results described below. For details, see Appendix A.2.

[14]Unless otherwise stated, p-values in this section are based on the two-tailed Wilcoxon-Mann-Whitney

Treatment	*Baseline*	*Arbitrator-* *36*	*56*	*36N*	*56N*
Winning bid	36.57	29.33^{***}	13.10^{***+++}	26.19^{***}	$13.12^{***\diamond\diamond\diamond}$
	(1.08)	(3.66)	(2.05)	(3.01)	(1.84)
Freq. high quality	0.17	0.66^{***}	0.30^{++}	0.64^{***}	$0.40^{\diamond}$
	(0.16)	(0.11)	(0.21)	(0.14)	(0.22)
Buyer's increment					
Low quality	0.11	1.03^{*}	0.96		
	(0.11)	(1.68)	(1.30)		
High quality	8.01	6.07	6.44		
	(5.60)	(3.69)	(5.56)		
Buyer's profit	19.91	36.03^{***}	22.81^{+++}		
	(6.27)	(5.03)	(5.85)		
Seller's profit	6.98	10.35^{*}	9.24	9.22^{*}	9.69
	(0.88)	(3.30)	(4.21)	(2.07)	(3.74)
	[30.4]	[338.3]	[247.9]	[438.8]	[268.3]

Notes: Displayed are session means, standard deviations in parentheses, of the key outcomes for *Baseline*, *Arbitrator-36* and *Arbitrator-56* based on data from the last 20 rounds. *Buyer's increment* is defined as the buyer's price choice minus the winning bid. The values in the square brackets underneath *Seller's profit* are the sample variances (a measure of sellers' profit variability) based on individual transaction data from all procurement interactions. The p-values are based on the following non-parametric Wilcoxon-Mann-Whitney tests taking each session as one independent observation (8 sessions per treatment):
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, *-36 / 56 / 36N / 56N vs. Baseline.*
$^{+++}p < 0.001$, $^{++}p < 0.01$, $^{+}p < 0.05$, *-36 vs. 56.*
$^{\diamond\diamond\diamond}p < 0.001$, $^{\diamond\diamond}p < 0.01$, $^{\diamond}p < 0.05$, *-36N vs. 56N.*
There are no significant differences for the comparisons *-36 vs. 36N* or *-56 vs. 56N.*

Table 3: Main experimental results.

first moment, the distribution of bids in *Baseline* is stochastically larger than in *Arbitrator-36* (p-value < 0.001, Kolmogorov-Smirnov test), which is larger than in *Arbitrator-56* (p-value < 0.001, Kolmogorov-Smirnov test). This ranking is visible in Figure 3.

Result 1. *Winning bids are decreasing in the probability of receiving a contingent payment.*

In Figure 4, we present the time series of winning bids that accompany the equilibrium quality level.[15] In the *Baseline* treatment, winning bids are not significantly above

test for two-sample comparisons and the Wilcoxon Signed-Rank test for one-sample comparisons.

[15]We do not have a prediction for bids accompanying the non-equilibrium level.

the equilibrium bid level over the last 20 rounds (p-value = 0.195). In the *Arbitrator-36* and *Arbitrator-56* treatments, bids are significantly above the equilibrium level (p-values = 0.008). However, this difference is most pronounced in *Arbitrator-36*, where the average winning bid remains stable over time at circa 50% above the predicted level.

Result 2. *Winning bids are above the equilibrium level with a contingent payment contract.*

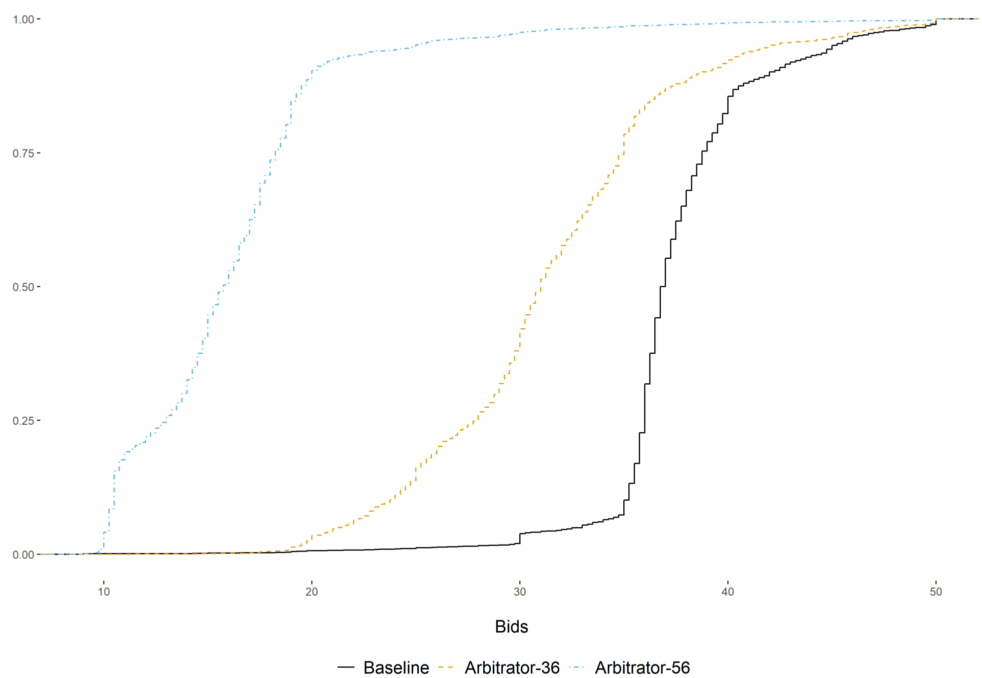

Figure 3: CDFs of auction bids.

Notes. Based on 3,360 bids per treatment.

Quality. Hypothesis 2 states that the frequency of high quality is greater in *Arbitrator-36* than in *Baseline* or *Arbitrator-56*. The data supports this hypothesis. In *Baseline*, only 17% of trading relationships were of high quality during the last 20 rounds. By contrast, high quality emerges as the majority procurement outcome in *Arbitrator-36*, comprising 66% of trading relationships. This frequency is significantly greater than in *Baseline* (p-value < 0.001). In *Arbitrator-56*, the frequency of high quality is 30% during the same period, which is significantly less than in *Arbitrator-36* (p-value = 0.007) and not significantly different

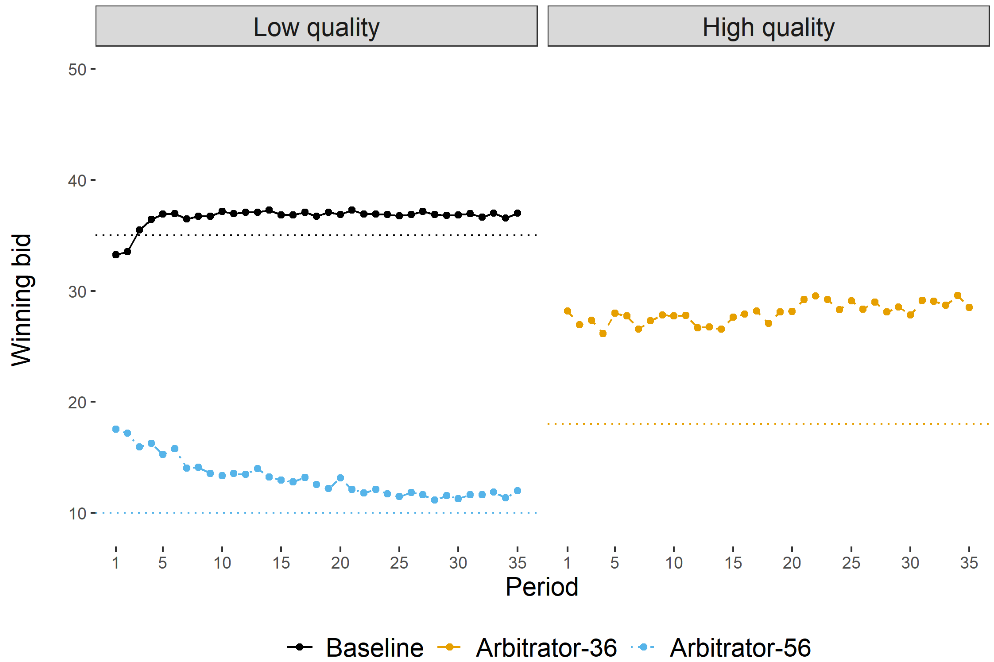

Figure 4: Winning bids associated with the equilibrium quality level over time.

Notes. The dotted line is the equilibrium bid level in each treatment.

from *Baseline* (p-value = 0.210).

Result 3. *Supplier quality is higher inside the "Goldilocks" region of the contingent contract.*

There are some interesting patterns in the quality data. The first is demonstrated by Figure 5. Across rounds 1 to 10 of the experiment, there is no significant difference in the average frequency of high quality trading relationships between *Arbitrator-36* and *Arbitrator-56* (p-value = 0.230), both of which are significantly greater than in *Baseline* (p-values < 0.01). By the last ten rounds, however, while the average frequency of high quality is 66% in *Arbitrator-36*, it falls to 24% in *Arbitrator-56*. The low rate of high quality trades in *Baseline* remains stable over time.[16]

Second, we observe differential auction selection effects among the three treatments. In *Baseline*, there is no significant difference between the rate of high quality chosen by

[16] Based on all 35 rounds, the frequency of high quality in *Arbitrator-56* (43%) is significantly greater than in *Baseline* (21%, p-value = 0.021). Nevertheless, the frequency of high quality in *Arbitrator-56* remains significantly less than in *Arbitrator-36* (61%, p-value = 0.021). See Table A1 for details.

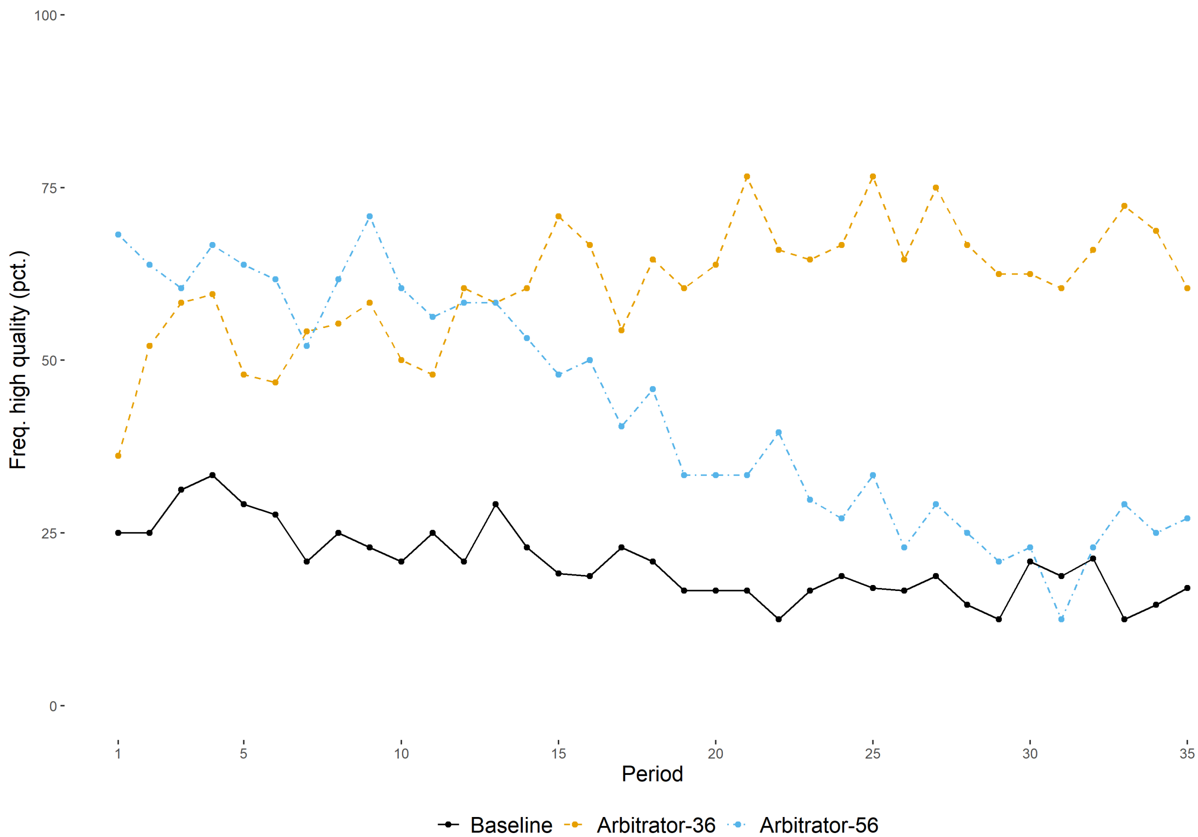

Figure 5: Percentage of high quality trading relationships over time.

Notes. Based on 1,680 trading relationships per treatment.

selected suppliers and non-selected suppliers during the auction stage (p-value = 0.742). In *Arbitrator-36*, high quality is chosen by 51.8% of non-selected suppliers after round 15, which is significantly *below* the rate of high quality among selected suppliers (p-value = 0.023). In *Arbitrator-56*, high quality is chosen by 57.7% of non-selected suppliers after round 15, which is significantly *above* the rate of high quality among selected suppliers (p-value = 0.008).

Figure 6 presents the distribution of winning bids in relation to trading quality, based on the last 20 rounds. Winning bids are grouped into seven buckets of six points, separately for each treatment. The bars represent the fraction of trades observed in a given bucket, stacked by quality level. Whereas there is no significant difference in winning bids by quality level in *Baseline*, we observe that lower bids are more likely to be associated with high quality

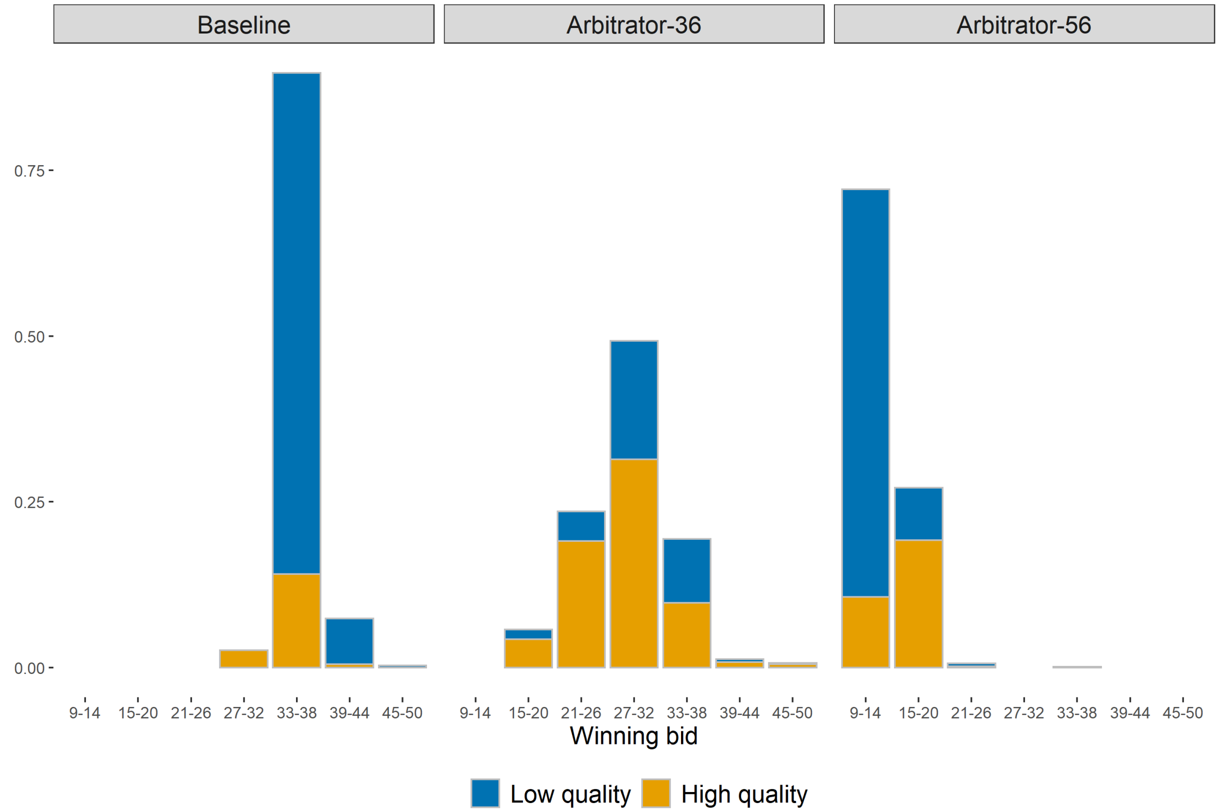

Figure 6: Distribution of winning bids (x-axis bid interval) in relation to trading quality (y-axis trade fraction) based on last 20 rounds.

trades in *Arbitrator-36* (p-value = 0.016). The reverse is true in *Arbitrator-56*, where lower bids are more likely to be associated with low quality trades (p-value = 0.016).

Pricing and profits. Hypothesis 3 states that it is buyers, and not sellers, who will gain from the higher quality trading relationships in *Arbitrator-36*. The data, however, suggests that both buyers and sellers can benefit.

We first examine the buyer's pricing decisions across the three treatments. Expressed as a voluntary increment over the winning bid, there are few differences among the three treatments. On average, buyers offer sellers close to zero for low quality, and an additional six to eight points for high quality. Within-subjects, the difference in buyer's increment between quality levels is significant for all treatments at the 5% level. Similar inferences may be made from the distribution of increments. We consider the existence of buyer reciprocity in detail in Section 5.2.

Consistent with Hypothesis 3, buyers earn significantly more in *Arbitrator-36* (36.03) than in *Baseline* (19.91, p-value < 0.001). The lower rates of high quality in *Arbitrator-56* mean that buyers in this treatment are not significantly better off than in the *Baseline* (22.81, p-value = 0.440) and earn less than in *Arbitrator-36* (p-value < 0.001). Based on Levene's test for equality of sample variances (Levene, 1960) using the transaction data from all procurement interactions, we find that sellers' profits are rank ordered in variance as *Arbitrator-36* > *Arbitrator-56* > *Baseline* (p-value < 0.001).

However, on average sellers also earn significantly more in *Arbitrator-36* (10.35) than in *Baseline* (6.98, p-value = 0.028). Thus, in contrast to Hypothesis 3, sellers are significantly better off in this treatment. In *Arbitrator-56*, seller profits are higher than in *Baseline* (9.24), but the difference is not significant (p-value = 0.190).[17] We obtain a final result.

Result 4. *Both buyers and sellers gain from a contingent payment contract designed to fall inside the "Goldilocks" region only.*

4.2 Robustness check: Results of the follow-up experiment

The results of the follow-up experiment with no buyer role (treatments *Arbitrator-36N* and *Arbitrator-56N*) are summarised in the final two columns of Table 3. The data in these treatments are qualitatively unchanged from the main treatments with a buyer role, an observation that we will return to in Section 5.2. All Results 1 to 4 continue to hold. In Appendix A.3, we replicate the results figures presented above using the follow-up experiment data and find similar patterns.

[17] If we consider data from all 35 rounds, then sellers also earn significantly higher profits in *Arbitrator-56* than in *Baseline* (p-value = 0.002). We cannot rule out that this is a facet of initial learning (see Figure 5).

5 Behavioural Model

5.1 Risk aversion and supplier bidding strategies

What can explain our finding that sellers in *Arbitrator-36* earn significantly higher profits than in *Baseline* or *Arbitrator-56* (Result 4)? Qualitatively, risk aversion may provide an explanation. Relative to the standard model based on expected payoff maximization, risk-averse suppliers would require a risk premium in their bids to compensate for the possibility of not realizing the quality-contingent payment. This would also be consistent with our observation from Figure 4 that bids remain robustly above the equilibrium level over time in *Arbitrator-36*.

To formally test this conjecture, we harness the individual-level auction data (approximately 3,330 bid-quality pairs per treatment) and embed a risk aversion model into a Quantal Response Equilibrium (QRE) framework (McKelvey and Palfrey, 1995).[18] This framework permits noise in the decision-making process. Our approach builds on Goeree et al. (2003), who proposed an extension of the QRE framework to incorporate risk aversion in a normal-form game setting, and Chowdhury et al. (2014), who applied the framework to contest data.[19] To begin, we assume that the final payment is fully determined by the outcome of the contract in (3), i.e., buyers in the experiment are believed to act as expected profit-maximizers. We assume a constant relative risk aversion (CRRA) utility function,

$$U(x) = \frac{x^{1-r}}{1-r}, \tag{5}$$

where r is the risk aversion parameter. Thus, $r = 0$ corresponds to the normative benchmark of risk neutrality, $r > 0$ indicates risk aversion and $r < 0$ indicates risk seeking. CRRA utility has previously been applied to auction data from the field (e.g., Campo et al., 2011) and the

[18]The small variation in number of observed bid-quality pairs among treatments is due to the use of a hard time-out protocol in the decision stages of the experiment. The rate of data loss is less than one percent in all treatments.

[19]See Moffatt (2015), Chapter 16, for more details.

lab (e.g., Chen and Plott, 1998).

In the auction stage, each supplier i forms a belief about the probability distribution over bidding strategies of his or her competitor, from which i calculates his or her expected utility based on (5) and conditional on winning the contract. Let the discrete bidding strategy set be indexed by j with cardinality J. A strategy s is a bid and quality tuple (b, q) for $b \in \{9, 9+\Delta, \ldots, 50-\Delta, 50\}$ and $q \in \{q^L, q^H\}$. The values of s are $s^1 = (9, q^L), s^2 = (9, q^H), \ldots, s^{J-1} = (50, q^L), s^J = (50, q^H)$, and the probability distribution is denoted by $p^1, p^2, \ldots, p^{J-1}, p^J$. The expected utility to player i of choosing a strategy s^k is:

$$EU_i(s^k; w_S; p^1, ..., p^J) = (1 - F(s^k))U(\pi_S) + F(s^k)U(w_S), \quad k \in \{1, 2, ..., J\}, \tag{6}$$

where the conditional probability of losing the auction is (after adjusting for ties):

$$F(s^k) = \begin{cases} \sum_{j=1}^{k-1} p^j + (p^k + p^{k+1})/2, & q = q^L; \\ \sum_{j=1}^{k-2} p^j + (p^k + p^{k-1})/2, & q = q^H. \end{cases} \tag{7}$$

According to the QRE model, the probability that player i chooses strategy s^k may then be expressed as:

$$p_i(s^k; w_S; p^1, ..., p^J; \lambda) = \frac{e^{\lambda EU_i(s^k)}}{\sum_{m=1}^{J} e^{\lambda EU_i(s^m)}}, \quad k \in \{1, 2, ..., J\}. \tag{8}$$

The noise parameter is λ and is inversely related to the level of decision error. For given estimated values $\hat{\lambda}$ and $\hat{r}$, the QRE is given by the vector of probabilities which constitutes a fixed point. If we define this vector by $\boldsymbol{p}^k(\hat{\lambda}, \hat{r})$, then the log-likelihood for our pooled sample of N bidding strategies is:

$$LL(\hat{\lambda}, \hat{r}) = \sum_{i=1}^{N} \sum_{k=1}^{J} \mathbb{1}(s_i = s^k) ln(\boldsymbol{p}^k(\hat{\lambda}, \hat{r})). \tag{9}$$

To mitigate issues of serial correlation due to initial learning, we estimate the QRE model on the last 20 rounds of auction data.[20] A computational difficulty in estimating the QRE model on auction data is the size of the strategy space, which for $\Delta = 0.25$ consists of 330 possible bid and quality combinations. To reduce the size of the strategy space, we follow a two-step process.

First, we round all bids to the nearest one point. The risk-neutral Nash equilibrium strategy holds under this restriction as the level of decision error goes to zero. Second, we limit attention to bids submitted in the 5-90 percentile range. Greater weight is assigned to the lower end of the distribution based on our observation that average bids are higher than predicted. For details, see Appendix A.4.

We fit the risk-averse QRE model for each treatment using maximum likelihood estimation. In support of our initial conjecture, we find significant risk aversion among suppliers in *Arbitrator-36* ($\hat{r} = 0.235$). We find no evidence of risk aversion in *Arbitrator-56*: the risk aversion parameter is not significantly different from zero ($p = 0.215$). This is intuitive: if the arbitrator is available on five out of six transactions, then the risk of not realizing a contingent payment on any one transaction is small. In *Baseline*, by contrast, we find significant risk seeking behaviour ($\hat{r} = -0.692$).[21] Based on likelihood ratio tests, the risk-averse QRE model provides a significantly better fit than a restricted model that allows for decision errors only in *Baseline* ($p < 0.001$) and in *Arbitrator-36* ($p < 0.001$), but not in *Arbitrator-56* ($p = 0.202$).

To further evaluate model performance, in Table 4 we provide the bid and quality predictions from the risk-averse QRE model. The lower part of the table displays the parameter estimates on which the predictions are based. We compare the predicted values to the average observed bid and quality statistics in all 35 rounds of each treatment. These comparisons permit an in- and out-of-sample test of our behavioural model. The predicted bids are close to the actual values observed: 38.91 versus 37.53 in *Baseline*, 31.56 versus 31.37 in *Arbitrator-36*, and 15.05 versus 16.18 in *Arbitrator-56*. For high quality, predicted versus

[20] See Davis (2015, p. 334) for a similar approach

[21] We will discuss this observation in Section 5.2.

Treatment	Baseline		Arbitrator-36		Arbitrator-56	
	Risk	Obs.	*Risk*	Obs.	*Risk*	Obs.
Model performance						
b_i	38.91	37.53	31.56	31.37	15.05	16.18
$q_i = q^H$	0.207	0.181	0.630	0.557	0.530	0.530
N	3,328		3,330		3,327	
Parameter estimates						
$\hat{\lambda}$	0.126^{***}		0.522^{***}		0.188^{***}	
	(0.016)		(0.033)		(0.030)	
$\hat{r}$	-0.692^{***}		0.235^{***}		-0.073	
	(0.090)		(0.010)		(0.059)	
N	1,680		1,656		1,757	
Log Likelihood	-4,267		-5,768		-5,051	
AIC	8,539		11,540		10,106	
BIC	8,550		11,551		10,117	

Notes: *** $p < 0.001$. Parameter estimates based on maximum likelihood estimation using data from the last 20 rounds. Standard errors across subjects reported in parentheses. *Risk* indicates the predicted values using the parameter estimates from the risk-averse QRE model. Obs. indicates the observed actual values based on bidding decisions in all 35 rounds.

Table 4: Risk-averse QRE model predictions and observed bid statistics by treatment.

observed frequencies are 0.21 versus 0.18 in *Baseline*, 0.63 versus 0.56 in *Arbitrator-36*, and 0.53 versus 0.53 in *Arbitrator-56*.

All of our results are robust to estimating the risk-averse QRE model on data from the *Arbitrator-36N* and *Arbitrator-56N* treatments (see Table A5).

5.2 Trust and performance-based reciprocity

As there is no objective risk in *Baseline*, there is reason to believe that the CRRA parameter estimate in this treatment may not be a preference for risk, but rather a display of trust in the buyer (see also Walker et al., 2022). To investigate this possibility, we consider an alternative formulation of the QRE model in which we introduce a parameter, $\gamma \geq 0$, that captures a supplier's belief about the buyer's voluntary increment that would be received for high quality. We will refer to this as the trust QRE model. Specifically, we assume that the

Treatment	Baseline[1]		Arbitrator-36[2]	Arbitrator-56[2]
	Trust	Obs.		
Model performance				
b_i	37.54	37.53		
$q_i = q^H$	0.227	0.181		
N	3,328			
Parameter estimates				
$\hat{\lambda}$	3.288***		0.474***	0.241***
	(0.108)		(0.028)	(0.016)
$\hat{\gamma}$	9.165***		-9.786***	-26.094***
	(0.047)		(0.323)	(2.756)
N	1,680		1,656	1,757
Log Likelihood	-4,024		-5,760	-4,996
AIC	8,053		11,524	9,997
BIC	8,064		11,535	10,008

Notes: *** $p < 0.001$. Parameter estimates based on maximum likelihood estimation using data from the last 20 rounds. Standard errors across subjects reported in parentheses. *Trust* indicates the predicted values using the parameter estimates from the trust QRE model. Obs. indicates the observed actual values based on bidding decisions in all 35 rounds.
[1]Non-negativity constraint imposed on trust parameter.
[2]Optimization unconstrained; model does not converge with non-negativity constraint on trust parameter. Thus, we cannot evaluate model performance.

Table 5: Trust QRE model predictions and observed bid statistics by treatment.

supplier expects to receive $(b + \gamma)$ conditional on winning and delivering high quality. Thus, we drop the restriction that the buyer is known to act as an expected profit-maximizer. We continue to assume that the buyer chooses zero increment for low quality.[22] As the buyer's increment cannot be negative, we restrict γ using the transformation $\hat{\gamma} = ln(\gamma)$ to keep the optimization problem unconstrained.

The results of this estimation are presented in Table 5. We find a significant positive level of supplier trust in *Baseline* ($\hat{\gamma} = 9.17$). The trust QRE model provides a better fit to the data for this treatment than the risk-averse QRE model based on log-likelihood, AIC and BIC values. Interestingly, the trust QRE model does not converge for *Arbitrator-36*

[22]The results are qualitatively unchanged by specifying a two-parameter trust model in which the supplier also forms a belief about the buyer's increment for low quality.

or *Arbitrator-56* when γ is constrained to be non-negative, which implies that this model is not a good fit for these treatments (and so we cannot compute predicted values). To obtain convergence, we must drop the non-negativity constraint. This yields trust parameter estimates of $\hat{\gamma} = -9.79$ in *Arbitrator-36* and $\hat{\gamma} = -26.09$ in *Arbitrator-56*.

The "negative trust" estimates in the arbitrator treatments are intuitive: if the supplier had expected to receive a positive increment from the buyer, then bidding would be more - not less - aggressive than predicted. Thus, we conclude that contingent payments substitute for trust, rather than complement it. Notice that this is consistent with the results of the follow-up experiment with no subject in a buyer role. If trust in the buyer's propensity to reciprocate is negligible, then assuming zero increment on the bid as in *Arbitrator-36N* and *Arbitrator-56N* would not significantly influence bidding behaviour. Indeed, we find no significant difference in bids or quality decisions between suppliers in *Arbitrator-36N* versus *Arbitrator-36* or in *Arbitrator-56N* versus *Arbitrator-56* (cf. Table 3).

Are the differential expectations of reciprocity with and without an arbitrator justified? To gain insight on this question, we estimate determinants of the buyer's voluntary increment as a function of the winning bid, quality and time. We estimate this model for each treatment using Tobit regression with the dependent variable left-censored at zero. We include session fixed effects and subject-level control variables for age, gender, family income status, academic major, self-reported risk preference and generalized trust attitudes (from the post-experiment questionnaire). We calculate robust standard errors and cluster these at the subject level.

The results of this analysis are presented in Table 6. After controlling for the bid level, the main determinant of the buyer's increment is the quality delivered. High quality is associated with significantly higher rewards from the buyer, which indicates some degree of performance-based reciprocity. However, the effect size is smaller in *Arbitrator-36* and *Arbitrator-56* than in *Baseline*. There is also an economically and statistically significant negative time trend in the buyer's increment in the treatments with an arbitrator, which is

Treatment	*Baseline*	*Arbitrator-36*	*Arbitrator-56*
Dependent variable		Buyer's increment	
Model	(1)	(2)	(3)
Winning bid	-0.69***	-0.71***	-0.11
	(0.19)	(0.14)	(0.44)
High quality	28.22***	13.57***	19.27**
	(2.77)	(2.96)	(5.91)
Period	-0.11	-0.28**	-0.53**
	(0.06)	(0.10)	(0.18)
Control variables	Yes	Yes	Yes
Session fixed effects	Yes	Yes	Yes
Observations	1,675	1,668	1,669
Subjects	48	48	48
Wald stat.	14.98***	14.05***	3.70***

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Coefficient estimates are presented, with robust standard errors in parentheses clustered at the subject level (48 clusters) to correct for intra-subject correlations. All models are estimated using Tobit regression, increment left-censored at zero, and include a constant term (not shown). *Buyer's increment* is defined as the buyer's price choice minus the winning bid. Subject-level controls are included for risk preference, age, gender, family income status, academic major and generalized trust.

Table 6: Determinants of the buyer's voluntary increment.

increasing in the probability of realizing a contingent payment; the negative time trend in *Baseline* is smaller and not significant at the 5% level.

In Appendix A.2, we provide more evidence from a series of random effects panel regressions at the individual-level to suggest that performance-based reciprocity is a significant driver of suppliers' bidding behaviour in our experiment. We also find that an independent (non-incentivized) measure of risk preferences elicited in the post-experiment questionnaire is correlated with suppliers' quality decisions in the *Arbitrator-36* treatment. This lends further support to the initial conjecture on risk aversion.

6 Concluding Remarks

The emergence of global supply chains and information technology allows enterprises to cast wider nets for and foster competition among suppliers. While harvesting price benefits, diminishing reliance on longer term procurement-supplier relationships and more frequent threats of contestability to suppliers increases susceptibility to supplier moral hazard which threatens efficiency gains. We introduce correlated contingent payment contracts (CCPCs) to potentially overcome this moral hazard even when there is price competition among suppliers. The key parameters of a CCPC are the probability of quality contingent payments, the flexibility of those contingent payments and the surplus division norm of those contingent payments. We examine the first two parameters and find there is a "Goldilocks" range for the implementation probability that yields high quality. Unlike previous proposed solutions that either rely upon the buyer and seller having social preferences or a repeated relationship, the CCPC works when the parties only seek to maximize the expected utility of their own payment and strategically backward induct. Our experiments largely confirm these predictions in the three ranges of the implementation probability with a surprising exception. In the high quality range, suppliers' economic profits are positive on average. We estimate a structural behavioural model that ex post shows risk averse sellers formulate bids that demand a risk premium for the uncertain payoffs for producing high quality.

The ideas of the CCPC are implicitly at the core of several procurement practices including third party arbitration with imperfect monitoring and contracts with retainage clauses. Also, contingent payments form an integral part of other real-world contracting institutions, such as "gainshare" arrangements in which pre-agreed rewards are tied to a subset of performance metrics (Carmichael, 2000; Sanderson et al., 2018). Our generalized and abstract analysis of CCPCs can arm managers with insights on how to approach potential supplier moral hazard while fostering price competition among suppliers. First, quality contingent prices are desirable but these must have imperfect correlation with actual quality. Second, the degree of the flexibility of contingent prices allowed in the contract needs to be sufficiently large. Third, the surplus share attribute of the contingent prices should reflect the fairness expectations of buyers and suppliers.

Our setup is stylised and this should also be considered when interpreting these results. To that end, there are several limitations of our model and experiment that it is particularly important to acknowledge. First, our model abstracts from private information and uncertainty about costs and values. Screening for exogenous aspects of quality is not the focus of this study – we explicitly assume an exogenous pre-qualification tender process.[23] Second, we do not consider trade-offs between economic and relational incentives in a repeated interaction. Thus, the managerial insights drawn from this study are most relevant for interactions where other-regarding preferences are less salient, such as in one-off infrastructure projects. Third, post-qualification, we assume that the supplier is selected based on price. Although a simplification, conditional on exogenous capability attributes, the formulation of bids based on surplus offered (capability minus price) is strategically equivalent to the first-price sealed bid auction in which bids are submitted based on price only (see Engelbrecht-Wiggans et al., 2007). Finally, we abstract from the contract negotiation process and relative bargaining powers post-auction, which could influence the effectiveness of contingent payments in practice. Future work might seek to address these limitations.

[23] See Zhang et al. (2021) for a theoretical treatment of the optimal pre-qualification mechanism.

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Appendix

A.1 Proofs of Propositions 1 and 2

Proof of Proposition 1. As quality cannot be verified, the seller anticipates the final price to be received at date 2, b, is independent of the quality level. Thus, the seller delivers low quality to minimise own unit cost. At Date 0, if all pre-qualified suppliers submit a bid equal to $c(q^L)$, then every supplier expects to earn zero profit net of the outside option. Any upward bid deviation would yield zero profit, due to the binding auction selection rule. Any unilateral downward bid deviation would yield less than the outside option and so is not profitable. Any equilibrium at a price above $c(q^L)$ cannot be sustained as there would be an incentive for any one supplier to undercut. Thus, the unique SPNE outcome of the non-contingent contract is $b_i^* = c(q^L)$ and $q_i^* = q^L$ for all i. $\square$

Proof of Proposition 2. At Date 1, the seller anticipates the final price to be received at Date 2 is determined by the contractual contingency in (3). At Date 0, all else equal, the seller has positive marginal returns from submitting a higher bid conditional on winning the auction.

The crux of the proof is to identify the region of parameters (α, σ) for which the price at which suppliers are indifferent to winning the contract conditional on delivering high quality lies strictly below the price at which suppliers are indifferent to winning the contract conditional on delivering low quality. That is, the break-even bid associated with high quality is lower than the break-even bid associated with low quality. Due to the binding selection rule, the no-deviation incentives at the lower (of the two) break-even bid are identical to Proposition 1: higher equilibrium bids are not possible because suppliers would have an incentive to undercut, and lower equilibrium bids are not profitable. We can thus rule out any equilibrium in the region $b \geq z(q^L)$ as this would generate a strictly positive profit. From now on, we assume that $b < z(q^L)$. There are three cases to consider.

(a) First, suppose $\alpha b \geq z(q^H)$. The break-even bid for $q \in \{q^L, q^H\}$ is $b(q) = \frac{c(q) - \sigma z(q)}{(1-\sigma)}$, which is obtained by setting the seller's expected payoff in (4) equal to the outside option and solving for the bid. Thus, $b(q^H) < b(q^L)$ if and only if $\sigma \in (\frac{c(q^H)-c(q^L)}{z(q^H)-z(q^L)}, \frac{c(q^H)}{z(q^H)})$. In this case, $\alpha \geq \frac{(1-\sigma)z(q^H)}{c(q^H)-\sigma z(q^H)}$.

(b) Second, suppose $z(q^L) < \alpha b < z(q^H)$. The break-even bid for low quality is unchanged from case (a). The break-even bid for high quality is $b(q^H) = \frac{c(q^H)}{1+(\alpha-1)\sigma}$. Thus, $b(q^H) < b(q^L)$ if and only if $\sigma \in (\frac{c(q^H)-c(q^L)}{z(q^H)-z(q^L)}, \frac{c(q^L)}{z(q^L)})$ and $\alpha \geq 1 + \frac{c(q^H)-c(q^L)-\sigma(c(q^H)-z(q^L))}{\sigma(c(q^L)-\sigma z(q^L))}$. Notice that the upper bound of the domain for σ in this case is greater than in case (a) because $\frac{c(q^L)}{z(q^L)} > \frac{c(q^H)}{z(q^H)}$ by equation (2).

(c) Third, suppose $\alpha b < z(q^L)$. Thus, $b(q^H) < b(q^L)$ if and only if $c(q^H) < c(q^L)$, which is a contradiction. This case is not relevant.

Now denote the level at which the condition on α binds in case (a) as a function of σ by $\alpha_a(\sigma) = \frac{(1-\sigma)z(q^H)}{c(q^H)-\sigma z(q^H)}$. Similarly, denote the level at which the condition on α binds in case (b) as a function of σ by $\alpha_b(\sigma) = 1 + \frac{c(q^H)-c(q^L)-\sigma(c(q^H)-z(q^L))}{\sigma(c(q^L)-\sigma z(q^L))}$. The two constraints are equal at $\sigma = \frac{c(q^H)-c(q^L)}{z(q^H)-z(q^L)}$. For any $\sigma > \frac{c(q^H)-c(q^L)}{z(q^H)-z(q^L)}$ in the intersection of the domains, $\alpha_b(\sigma) < \alpha_a(\sigma)$ and so $\alpha_b(\sigma)$ is the binding constraint. For any $\sigma < \frac{c(q^H)-c(q^L)}{z(q^H)-z(q^L)}$, $\alpha_b(\sigma) > \alpha_a(\sigma)$, in which case $\alpha \geq \frac{(1-\sigma)z(q^H)}{c(q^H)-\sigma z(q^H)}$ and we would require $\sigma > \frac{c(q^H)-c(q^L)}{z(q^H)-z(q^L)}$ for high quality to be an equilibrium outcome, which is a contradiction. Thus, the sufficient conditions for high quality to be the unique equilibrium outcome are given in the proposition, where $\alpha_{min}(\sigma) = \alpha_b(\sigma)$. $\square$

A.2 Supplemental data: Main experiment

A.2.1 Treatment effects

Treatment	*Baseline*	*Arbitrator-36*	*Arbitrator-56*
Winning bid	35.92	28.68***	14.42******
	(1.24)	(2.78)	(1.66)
Freq. high quality	0.21	0.61***	0.43*+
	(0.15)	(0.10)	(0.14)
Buyer's increment			
Low quality	0.18	1.39**	1.31**
	(0.14)	(1.69)	(1.04)
High quality	11.18	6.32*	6.34
	(4.09)	(3.70)	(4.56)
Buyer's profit	21.56	33.28***	25.60++
	(6.14)	(3.72)	(3.21)
Seller's profit	6.71	11.13**	11.60**
	(0.62)	(2.52)	(3.04)

Notes: Displayed are session means, standard deviations in parentheses, of the key outcomes for *Baseline*, *Arbitrator-36* and *Arbitrator-56* based on data from all 35 rounds. *Buyer's increment* is defined as the buyer's price choice minus the winning bid. The p-values are based on the following non-parametric Wilcoxon-Mann-Whitney tests taking each session as one independent observation:
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, *-36 / 56 vs. Baseline.*
$^{+++}p < 0.001$, $^{++}p < 0.01$, $^{+}p < 0.05$, *-36 vs. 56.*

Table A1: Session averages (mean and standard deviation) based on all 35 rounds.

	(1) Winning bid	(2) High quality	(3) Final price	(4) Buyer's profit	(5) Seller's profit
Arbitrator-36	-7.241***	0.487***	8.229***	16.141***	3.355**
	(1.289)	(0.065)	(1.394)	(2.711)	(1.153)
Arbitrator-56	-23.472***	0.129	3.559	2.910	2.265
	(0.782)	(0.089)	(2.120)	(2.898)	(1.456)
Period	-0.003	-0.004*	0.000	-0.203**	0.041
	(0.020)	(0.002)	(0.066)	(0.068)	(0.054)
Constant	36.658***	0.276***	38.695***	25.102***	5.935***
	(0.683)	(0.072)	(1.768)	(2.771)	(1.404)
Observations	2880	2867	2867	2867	2867
R-squared	0.888	0.183	0.047	0.109	0.010
p-value	0.000	0.000	0.059	0.000	0.553

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Coefficient estimates are presented with robust standard errors in parentheses clustered at the session level (24 clusters) to correct for intra-session correlations. The reference treatment is *Baseline*. The models are estimated using OLS. The p-value in the final row of the table is from a linear hypothesis test for equality of coefficient estimates between *Arbitrator-36* and *Arbitrator-56*. In columns (2) to (5), trade data from 13 matching groups is lost due to the hard time-out protocol.

Table A2: Regression analysis of matching group data based on last 20 rounds.

A.2.2 Session-level heterogeneity

To obtain insight into heterogeneity among the 8 market sessions in each treatment, in Figures A1, A2 and A3 we present procurement outcomes for every session in each treatment separately. A data point in each panel is the outcome of a single interaction group for a given period.

In *Baseline*, most sessions fail to sustain high quality as the session progresses; in 2 out of 8 sessions, buyers noticeably reward suppliers for high quality with a higher final price and this enables a minority fraction of high quality trades to emerge in these sessions (the largest fraction being 42.5%). The range of average winning bids in this treatment is 34.8 to 37.9, and for final prices, 35.8 to 41.6.

In *Arbitrator-36*, there is a majority fraction of high quality trades in every session (the smallest fraction being 52.1%). The range of average winning bids in this treatment is 21.8 to 33.1, and for final prices, 41.4 to 52.5.

In *Arbitrator-56*, winning bids are consistently low across sessions in this treatment (range 11.3 to 16.2) and there is a majority fraction of low quality trades in 6 out of 8 sessions (the smallest fraction being 9.2% and the highest fraction being 61.7%). The range of average final prices in this treatment is 34.9 to 52.6.

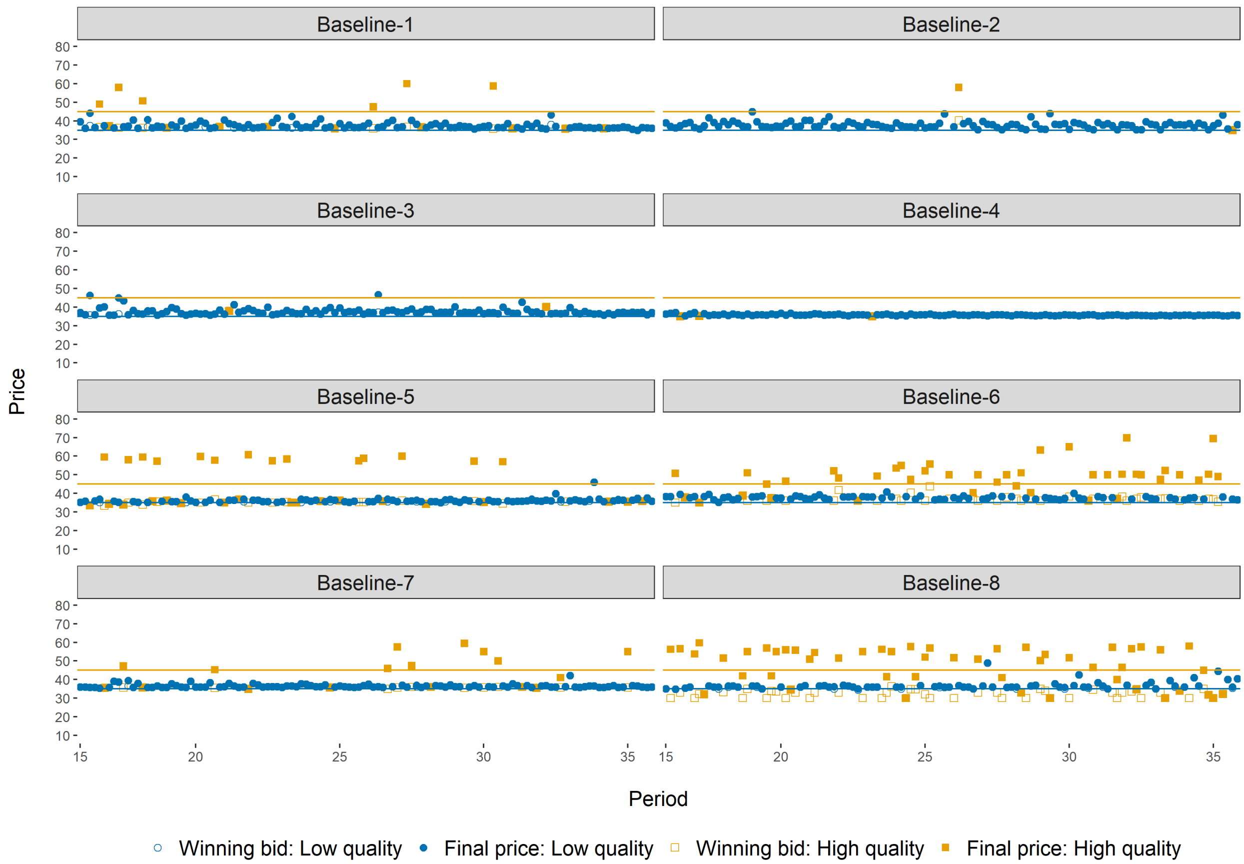

Figure A1: Market outcomes in the 8 sessions of the *Baseline* treatment.

Notes. Based on last 20 rounds.

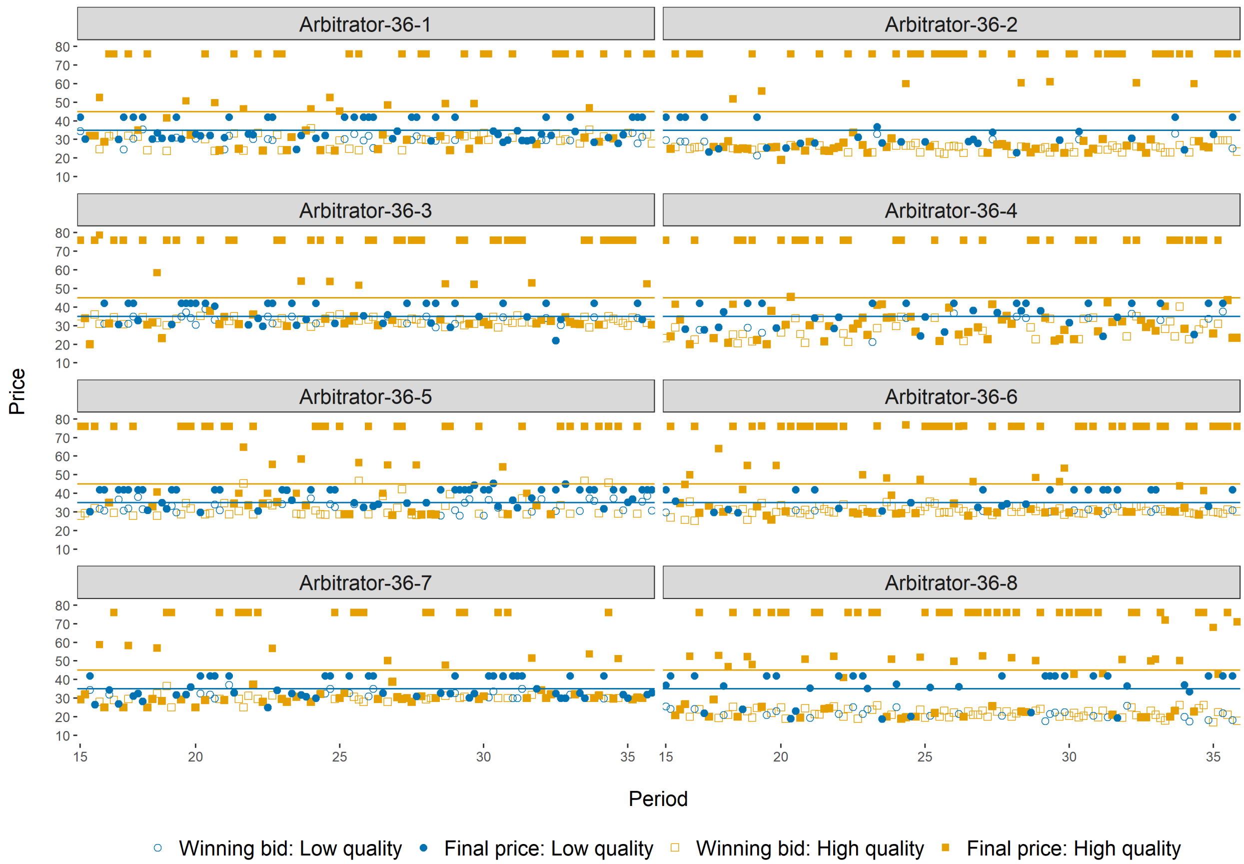

Figure A2: Market outcomes in the 8 sessions of the *Arbitrator-36* treatment.

Notes. Based on last 20 rounds.

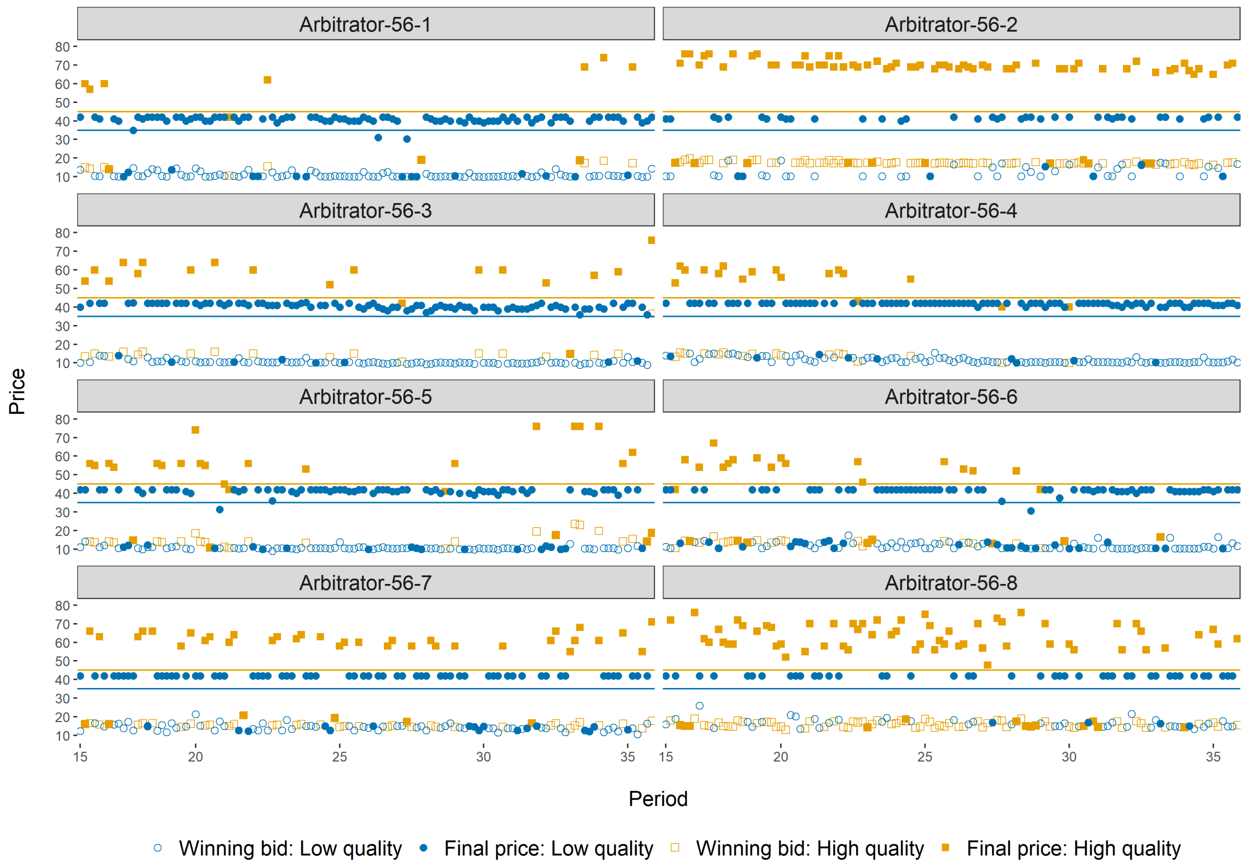

Figure A3: Market outcomes in the 8 sessions of the *Arbitrator-56* treatment.

Notes. Based on last 20 rounds.

A.2.3 Individual-level regression analysis of bidding strategies

In this section, we estimate random effects panel regressions to determine the main factors influencing the bid and high quality decisions of supplier i in period t. We use a linear regression specification for the bid determinants and a logistic specification for the quality determinants.

We consider specifications in which the regressors are either unconditional or conditional on winning the contract in the previous period. The unconditional regressors are the once-lagged competitor's bid, a dummy for winning the contract in the previous period and a time trend; for the conditional specifications, we include the once-lagged continuous buyer's increment. The once-lagged competitor's bid is used to circumvent the endogeneity problem of including a lagged dependent variable in the bid regression and the simultaneity issue of including the contemporaneous own bid in the quality regression. A few observations are lost due to the use of a hard time-out protocol in the decision phase of the experimental sessions. The rate of data loss is less than one percent in all treatments. Regressions that include the once-lagged buyer's increment are based on a reduced sample size. This provides a measure of path-dependent reciprocity, which might plausibly influence the evolution of bidding strategies over time if this changes a supplier's beliefs about expected payoffs.

In Figure A4, we plot the resulting point estimates and 95% confidence intervals for the main predictor variables. The regression results tables are contained in Tables A3 and A4. We observe a significant positive dependency of current bids on the once-lagged competitor's bid in all treatments, which captures the strategic complementarities of price competition. There is no robust evidence of a trend in the bid level over time in either *Baseline* or *Arbitrator-36*. The fraction of high quality choices is decreasing over time in *Baseline*, increasing over time in *Arbitrator-36*, and decreasing over time in *Arbitrator-56*. There is also a significant positive relationship between a subject's stated willingness to take risks and his or her probability of choosing high quality in *Baseline* and *Arbitrator-36*. This positive correlation is no longer significant in *Arbitrator-56*. The buyer's choice of a higher increment in the previous period is associated with a significantly greater probability of the contracting supplier delivering high quality in the next (and unrelated) trading period. The effect size is decreasing in the probability of receiving a contingent payment, falling from 5.5% to 2.1% in *Arbitrator-36* and just 1.7% in *Arbitrator-56*. This indicates differential expectations of buyer reciprocity with and without a contingent payment contract.

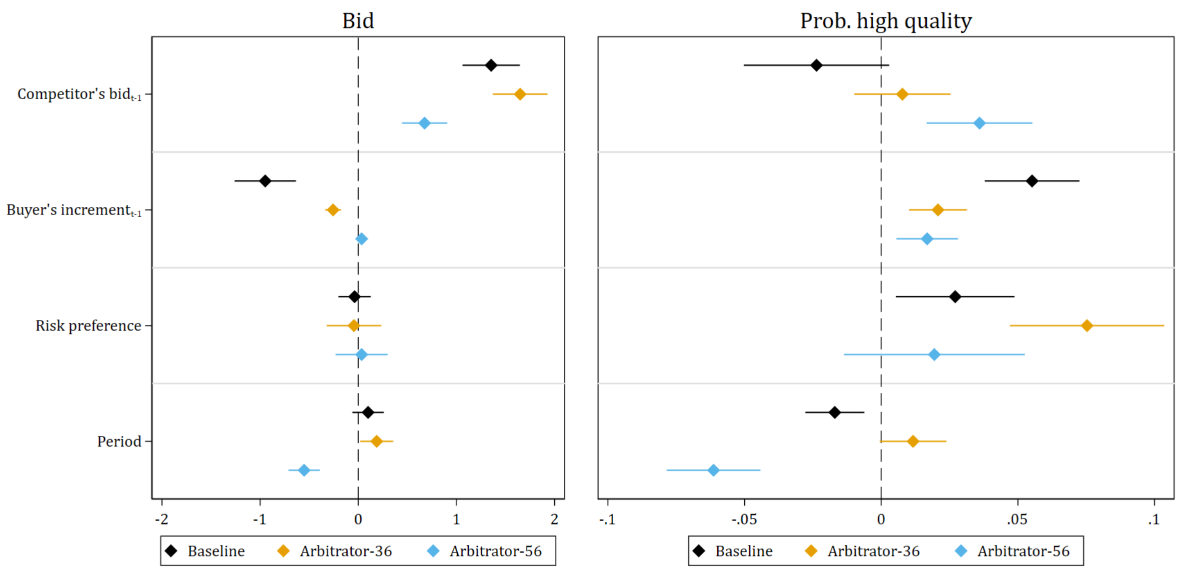

Figure A4: Main determinants of suppliers' bidding strategies.

Notes. Bid panel: coefficient estimates with 95% confidence intervals based on random effects linear regressions. Quality panel: average marginal effects with 95% confidence intervals based on random effects Logit regressions. Standard errors are clustered at the subject level (96 clusters) to correct for intra-subject correlations. *Buyer's increment* is defined as the buyer's price choice minus the winning bid. *Competitor's bid*$_{t-1}$, *Buyer's increment*$_{t-1}$ and *Period* are each divided by 5 in the estimation. Subject-level control variables are included for age, gender, family income status, academic major and generalized trust attitudes. See Table A4 for the underlying regression results.

Treatment	Baseline		Arbitrator-36		Arbitrator-56	
Dependent variable	Bid	High quality	Bid	High quality	Bid	High quality
Model	(1)	(2)	(3)	(4)	(5)	(6)
Competitor's bid$_{t-1}$	0.265***	-0.003*	0.362***	0.002	0.172***	0.009***
	(0.030)	(0.002)	(0.029)	(0.002)	(0.025)	(0.002)
Winner$_{t-1}$	-1.596***	0.004	-2.746***	-0.013	-0.840***	-0.047***
	(0.235)	(0.014)	(0.323)	(0.019)	(0.268)	(0.018)
Risk preference	-0.012	0.044***	-0.094	0.076***	-0.060	0.011
	(0.101)	(0.012)	(0.141)	(0.014)	(0.117)	(0.016)
Period	0.017	-0.004***	0.032*	0.002**	-0.089***	-0.009***
	(0.015)	(0.001)	(0.019)	(0.001)	(0.015)	(0.002)
Constant	23.496***		15.204***		20.794***	
	(2.007)		(3.466)		(2.827)	
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Session fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,233	3,233	3,237	3,237	3,232	3,232
Number of subjects	96	96	96	96	96	96
Wald stat.	4855***	473.6***	416.7***	42.67***	252.7***	80.07***

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Coefficient estimates are presented with robust standard errors in parentheses clustered at the subject level (96 clusters) to correct for intra-subject correlations in the estimation. Models (1), (3) and (5) are estimated using random effects linear regression. Models (2), (4) and (6) are estimated using random effects Logit regression and average marginal effects are presented. Subject-level control variables are included for risk preference (shown), age, gender, family income status, academic major and generalized trust attitudes.

Table A3: Determinants of bidding strategies (unconditional on trade in prior period).

Treatment	Baseline		Arbitrator-36		Arbitrator-56	
Dependent variable	Bid	High quality	Bid	High quality	Bid	High quality
Model	(1)	(2)	(3)	(4)	(5)	(6)
Competitor's bid$_{t-1}$	1.354***	-0.024*	1.649***	0.008	0.676***	0.036***
	(0.149)	(0.014)	(0.142)	(0.009)	(0.118)	(0.010)
Buyer's increment$_{t-1}$	-0.948***	0.055***	-0.257***	0.021***	0.034	0.017***
	(0.160)	(0.009)	(0.041)	(0.005)	(0.024)	(0.006)
Risk preference	-0.038	0.027**	-0.044	0.075***	0.034	0.019
	(0.084)	(0.011)	(0.142)	(0.014)	(0.135)	(0.017)
Period	0.100	-0.017***	0.188**	0.012*	-0.552***	-0.061***
	(0.082)	(0.006)	(0.086)	(0.006)	(0.082)	(0.009)
Constant	24.482***		12.712***		21.860***	
	(2.067)		(3.241)		(3.176)	
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Session fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,609	1,609	1,601	1,601	1,603	1,603
Number of subjects	96	96	96	96	96	96
Wald stat.	10400***	454.2***	462.9***	51.32***	231***	90.07***

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Coefficient estimates are presented with robust standard errors in parentheses clustered at the subject level (96 clusters) to correct for intra-subject correlations. *Buyer's increment* is defined as the buyer's price choice minus the winning bid. *Competitor's bid*$_{t-1}$, *Buyer's increment*$_{t-1}$ and *Period* are each divided by 5 in the estimation. Models (1), (3) and (5) are estimated using random effects linear regression. Models (2), (4) and (6) are estimated using random effects Logit regression and average marginal effects are presented. Subject-level control variables are included for risk preference (shown), age, gender, family income status, academic major and generalized trust attitudes.

Table A4: Determinants of bidding strategies (conditional on trade in prior period).

A.3 Supplemental data: Follow-up experiment with no buyer role

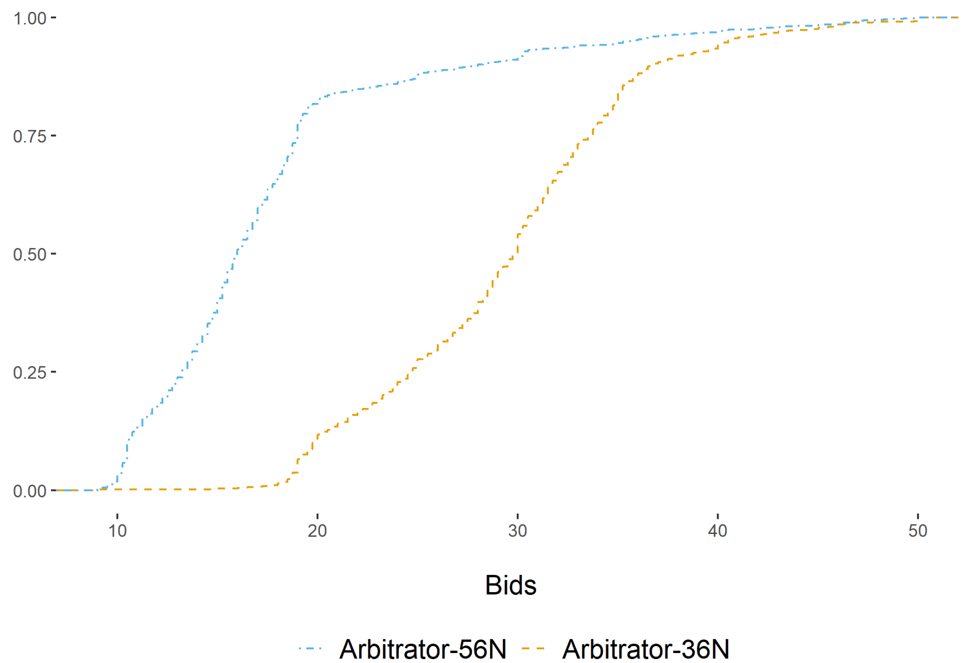

Figure A5: CDFs of auction bids in the treatments with no buyer.

Notes. Based on 3,360 bids per treatment.

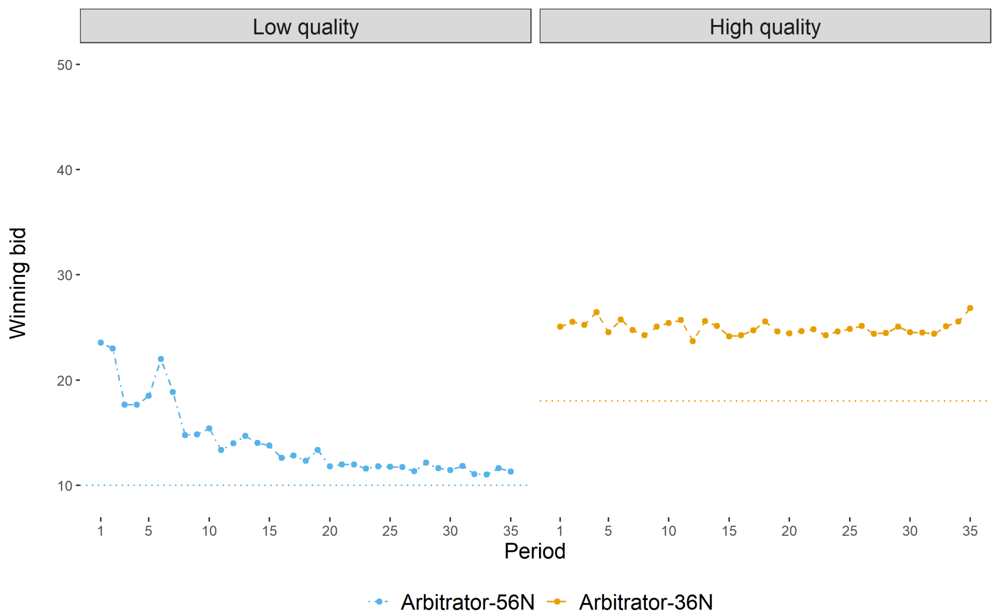

Figure A6: Winning bids associated with the equilibrium quality level over time in the treatments with no buyer.

Notes. The dotted line is the equilibrium bid level in each treatment.

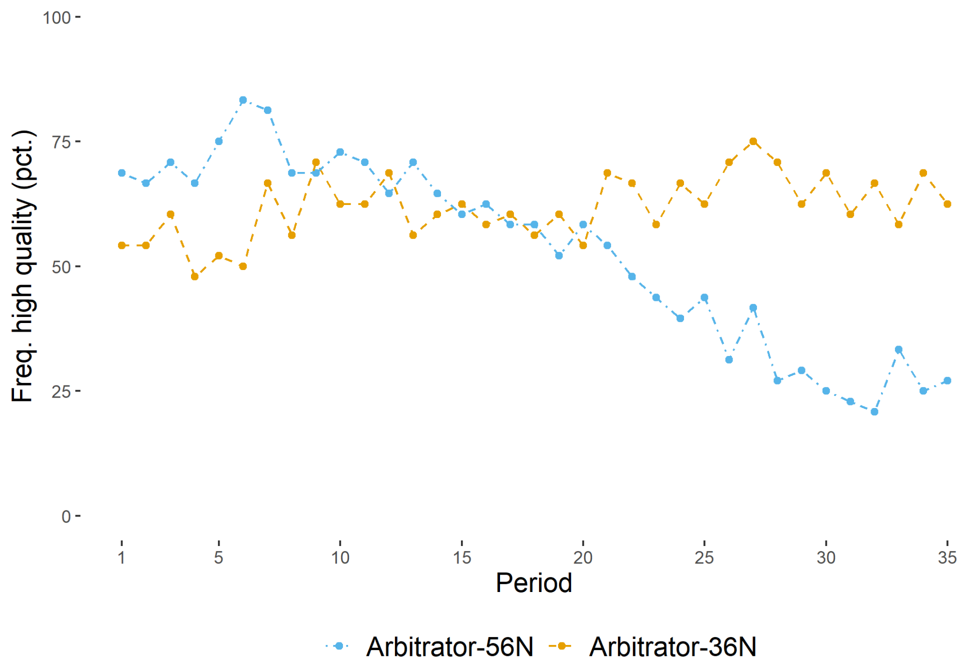

Figure A7: Percentage of high quality trading relationships over time in the treatments with no buyer.

Notes. Based on 1,680 trading relationships per treatment.

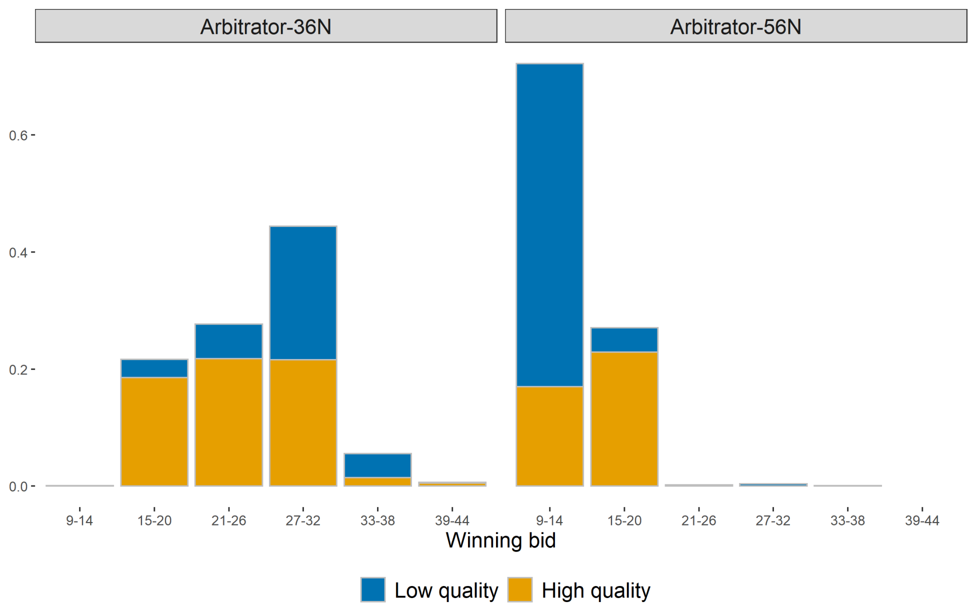

Figure A8: Distribution of winning bids (x-axis bid interval) in relation to trading quality (y-axis trade fraction) based on last 20 rounds in the treatments with no buyer.

A.4 Additional details about the behavioural model estimation

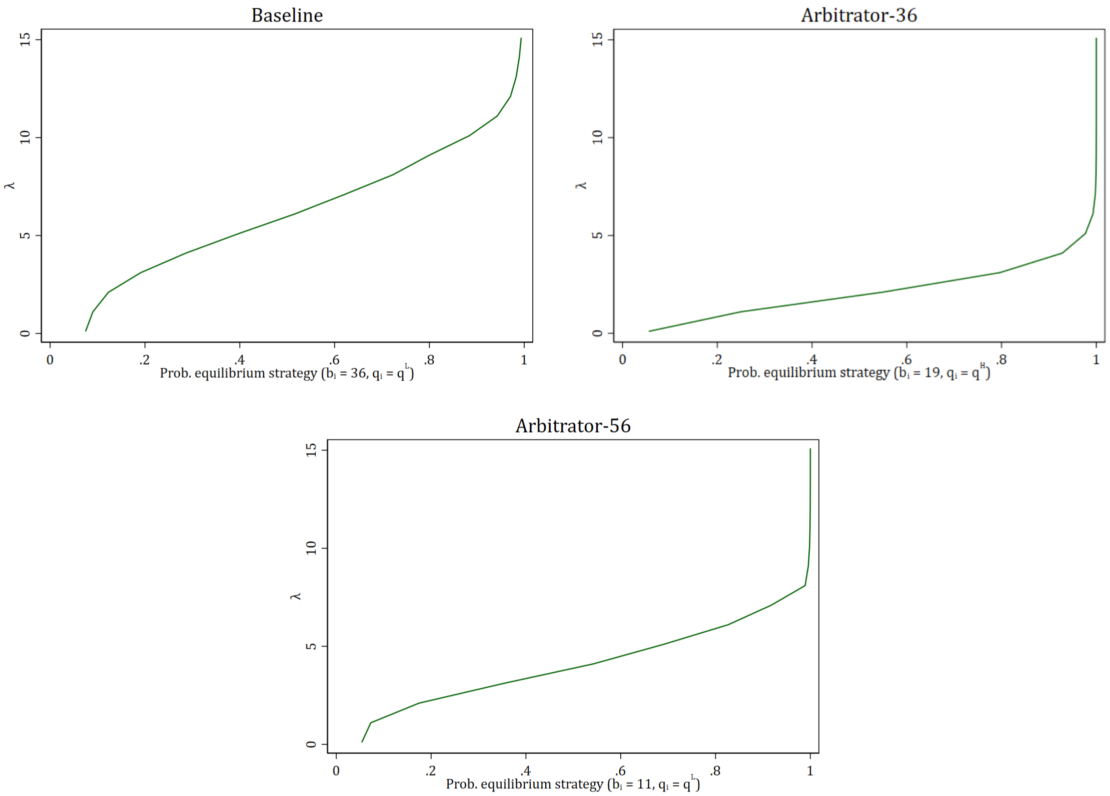

Figure A9: Probability of choosing the Nash equilibrium bid and quality level as the parameter λ (inversely related to the level of decision error) increases.

Notes. Based on MATA routine to find the vector of bidding strategy probabilities (bid and quality) for the given treatment that correspond to a fixed point, assuming that all suppliers evaluate strategies based on relative expected utilities and this is common knowledge. Δ is set equal to one point.

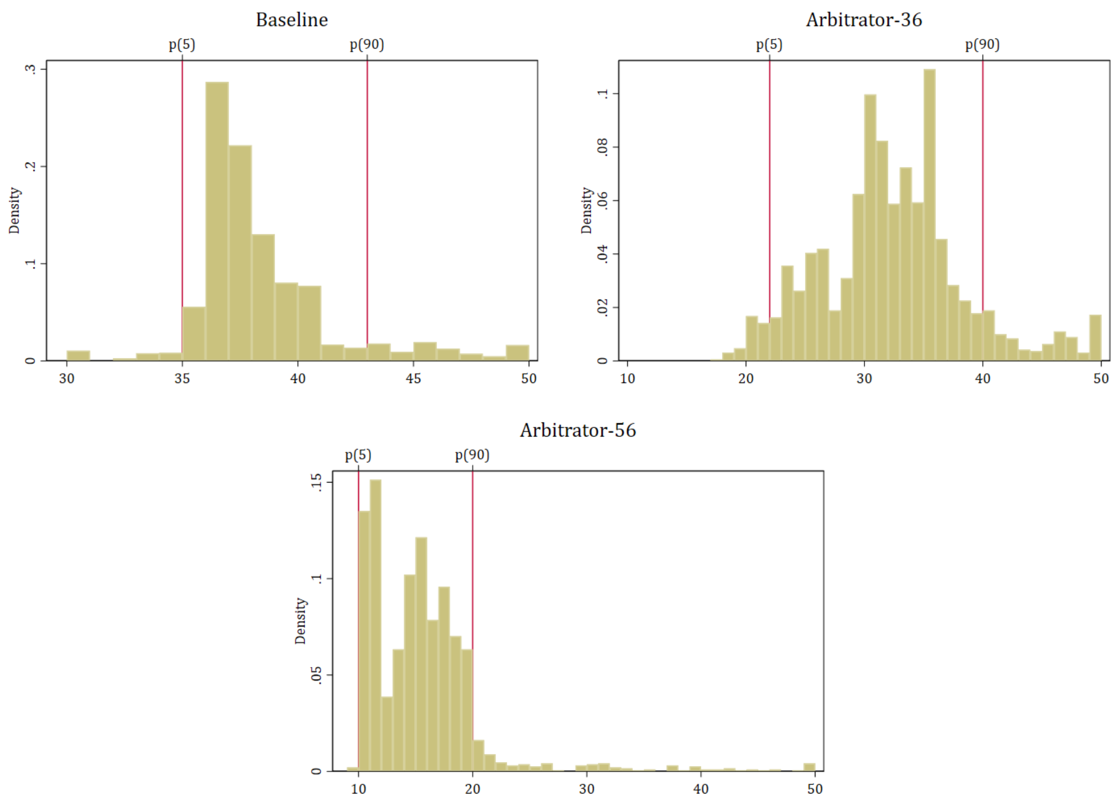

Figure A10: Histogram of included bid strategy components in the behavioural model estimation (5-90 percentile).

Treatment	Arbitrator-36N		Arbitrator-56N	
	Risk	Obs.	*Risk*	Obs.
Model performance				
b_i	30.78	29.39	15.10	17.75
$q_i = q^H$	0.613	0.551	0.561	0.594
N	3,324		3,324	
Parameter estimates				
$\hat{\lambda}$	0.257^{***}		0.275^{***}	
	(0.029)		(0.030)	
$\hat{r}$	0.146^{***}		-0.063	
	(0.021)		(0.043)	
N	1,558		1,723	
Log Likelihood	-5,517		-4,856	
AIC	11,037		9,716	
BIC	11,048		9,727	

Notes: *** $p < 0.001$. Parameter estimates based on maximum likelihood estimation using data from the last 20 rounds. Standard errors across subjects reported in parentheses. *Risk* indicates the predicted values using the parameter estimates from the risk-averse QRE model. Obs. indicates the observed actual values based on bidding decisions in all 35 rounds.

Table A5: Risk-averse QRE model predictions and observed bid statistics by treatment in the follow-up experiment with no buyer role.

A.5 Additional details about the experiment

A.5.1 Procedural details for the experimental sessions

At the start of a session, subjects read the instructions and had to answer a set of eight comprehension questions correctly before proceeding to the practice periods. Each round was divided into two decision stages. In the first stage, suppliers submitted their prices. At the same time as choosing a price, each supplier also chose a quality level, low or high, to be delivered conditional on winning the contract. This variant on the strategy method enabled twice as many quality observations to be collected, without changing the strategic nature of the game. The supplier who submitted the lower price won the auction and became the seller, with ties broken randomly. The winning and losing bids and the minimum payment obligation were then revealed within the group. This information was presented to subjects as a contract price range, with the lower bound price equal to the winning bid (price floor) and the upper bound price equal to four times the winning bid (price ceiling). The supplier submitting the losing bid earned his outside option.

In the second stage, the buyer observed the seller's chosen quality level and chose a price from the contract price range. In *Baseline*, the buyer's choice was the final price. In *Arbitrator-36* and *Arbitrator-56*, subjects were informed that an independent third party Arbitrator (outside of the experiment) has set a reference price, which depends on the winning supplier's quality. If the buyer's price choice is below the reference price, then the Arbitrator may intervene to assign a final price equal to the reference price, constrained by the bounds of the contract. The Arbitrator was available to intervene on three out of six transactions in *Arbitrator-36*, and five out of six transactions in *Arbitrator-56*.[24] The reference price in any transaction is the amount from the contract price range which minimises the distance between the buyer's price choice and equation (2). Subjects were informed of the reference price level but not the equation used to determine it. The probabilistic nature of the Arbitrator was explained to subjects using a standard six-sided die roll.

To illustrate, suppose the winning bid is 32 and the seller selects high quality. The contract price range is [30, 120]. The buyer chooses a price of 65, but the Arbitrator's price is 76. In *Baseline*, the buyer's price choice is the final price: the buyer earns 35 and the seller earns 25. In *Arbitrator-36* and *Arbitrator-56*, a die is rolled to determine whether the Arbitrator is available to intervene. If the Arbitrator is available, then the Arbitrator's price is the final price: the buyer earns 24 and the seller earns 36. If the Arbitrator is not available, then the buyer's price choice is the final price and earnings are the same as in *Baseline*.

At the end of each round, feedback was provided about the outcomes of a subject's own

[24] Two-tailed binomial tests confirm that the randomization was successful.

Role / Treatment	*Baseline*	*Arbitrator-36*	*Arbitrator-56*
Buyer	945.07	1349.98	1092.96
Supplier	409.96	489.59	492.68

Table A6: Average experimental points earned by treatment and role.

interaction group on bids, quality, price, and profits. This feedback was provided to all groups simultaneously, to prevent subjects inferring the identities of others in their group. Private feedback remained available in a history table to facilitate learning. The losing supplier only observed the auction outcome. Horizontal sliders were used for the suppliers' bidding decision and the buyer's price choice. The initial values of these sliders were set at random in each interaction to avoid anchoring bias.

Subject payments' were transferred to a subject's Ancademy account within 24 hours of the experiment, accessible via WeChat pay. The total points from all rounds were multiplied by a pre-determined exchange rate of 30 points per 1 RMB for subjects in a buyer role, and 15 points per 1 RMB for subjects in a supplier role.[25] As is often the case in auction experiments, there is the possibility of losses. All subjects were therefore endowed with 200 points at the onset of the first (non-practice) round. Subsequent profits/losses were then added to or subtracted from the endowment. Subjects were informed that if their losses exceeded their initial points endowment, then they would only receive the show-up fee. In practice, this was never a binding constraint (the minimum number of points accrued by a subject in any session was 310 points). The average points accrual, split by treatment and role, is presented in Table A6.

A.5.2 Subject demographic characteristics

In the following tables, we present summary data on subject demographic characteristics and self-reported trust and risk attitudes for the main treatments, as elicited in the post-experiment questionnaire (equivalent statistics for the treatments with no buyer role are available on request). We find no statistically significant differences in subject demographics among the three treatments (the test statistics are available on request).

[25] The differential exchange rates compensate for the expectation that, on average, each supplier participates in half as many transactions as the buyer.

	Baseline	Arbitrator-36	Arbitrator-56
Mean	20.66	20.28	20.65
Std.Dev	1.78	1.98	1.66

Table A7: Age.

	Baseline	Arbitrator-36	Arbitrator-56
Female	73	79	91
Male	64	60	52

Notes: Data on gender is not available for 13 subjects.

Table A8: Gender.

	Baseline	Arbitrator-36	Arbitrator-56
Arts and Education	1	5	7
Business and Management	26	25	30
Economics and Finance	44	46	36
Engineering and Natural Sciences	44	37	39
Law and Social Sciences	20	28	27
Medicine and Health Sciences	9	3	5

Table A9: Academic major.

	Baseline	Arbitrator-36	Arbitrator-56
Far below average	3	7	6
Below average	42	41	40
Average	84	79	83
Above average	14	17	15
Far above average	1	0	0

Table A10: Parents' income at 16 years old in comparison to other families in the country.

	Baseline	Arbitrator-36	Arbitrator-56
Can't be too careful	63	69	67
Most people can be trusted	81	75	77

Table A11: Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?

	Baseline	Arbitrator-36	Arbitrator-56
Would take advantage of you	80	80	76
Would try to be fair	64	64	68

Table A12: Do you think most people would try to take advantage of you if they got a chance, or would they try to be fair?

	Baseline	Arbitrator-36	Arbitrator-56
Just look out for themselves	117	115	120
Try to be helpful	27	29	24

Table A13: Would you say that most of the time people try to be helpful, or that they are mostly just looking out for themselves?

	Baseline	Arbitrator-36	Arbitrator-56
More or less agree	84	68	68
More or less disagree	60	76	76

Table A14: You can't count on strangers anymore.

	Baseline	Arbitrator-36	Arbitrator-56
Mean	4.69	4.90	4.73
Std.Dev	2.08	2.34	2.07

Table A15: Are you generally a person who is fully willing to take risks or do you try to avoid taking risks?

	Baseline	Arbitrator-36	Arbitrator-56
Mean	4.18	4.49	4.09
Std.Dev	2.18	2.48	2.06

Table A16: How would you rate your willingness to take risks in financial matters?