Cooperation and Mistrust in Relational Contracts*

Holger Herz, Armin Schmutzler and André Volk

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Abstract

Work and trade relationships are often governed by relational contracts, in which incentives for cooperative action today stem from the prospective future benefits of the relationship. In this paper, we study how a lack of hard information about the costs of providing quality, and therefore about the financial consequences of actions, affects relational contracts in buyer-seller relationships. The absence of verifiable information can impede the joint understanding of what constitutes cooperative behavior, and may thus inject mistrust into relationships. Comparing seller-buyer relationships with hard (verifiable) and soft (non-verifiable) information about seller costs in the laboratory, we find that soft information affects the terms of relational contracts. The party with the informational advantage is able to adjust contractual terms to its advantage. However, these adjustments are not reciprocated with efficiency-reducing actions by the less informed party. We therefore find that asymmetric information only affects the distribution of rents, and not efficiency.

Keywords: Relational Contracts; Non-Verifiable Information; Experiments.

JEL Classification: D01, D03, L14, L20.

*Holger Herz (corresponding author): University of Fribourg, Department of Economics, Bd. de Perolles 90, Switzerland. holger.herz@unifr.ch. Armin Schmutzler: University of Zurich. armin.schmutzler@econ.uzh.ch. André Volk: University of Zurich. andre.volk@econ.uzh.ch.
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1 Introduction

The literature on relational contracts investigates the conditions under which cooperative and efficient behavior is sustainable through repeated interaction.[1] A general result in this literature is that it can be in everybody's self-interest to act cooperatively if it is common knowledge that, for each trading party, the individual future benefits of upholding the relational contract are sufficiently large. In this sense, upholding the relational contract is a matter of credibility. The literature discusses two ways to establish such credibility. The standard approach is to assume infinitely repeated interaction, so that cooperation can emerge as an equilibrium of the infinitely repeated game. A well-established alternative to this approach assumes that at least a subset of players has social preferences and intrinsically values sharing the rents, for example due to inequity aversion (Fehr and Schmidt, 1999).[2] With such preferences, cooperation can be sustained even in finite horizon settings (except in the final period).

In this paper, we study how asymmetric information affects the performance of relational contracts. In the presence of players with social preferences, sustaining cooperation relies on a fair split of the surplus. As long as both players obtain what they consider to be a fair share (say, an equal split), they are themselves willing to take actions that provide a fair share to the other player. However, this presupposes perfect information about each others' payoffs, so that parties have common knowledge about which actions actually generate a fair split. If players cannot infer payoffs from actions, for example because they lack information about payoff relevant parameters, coordination on fair actions becomes harder. Such informational asymmetry often seems plausible. For instance, in the workplace, a principal may not observe the effort costs of an agent. The cost of producing a certain output might be high for some agents, and low for others. Because the fair price depends on these costs, the principal can never be certain which wage implements a fair split of rents. With asymmetric information, it is therefore not obvious how parties can coordinate on fair behavior. One might therefore conjecture that efficient outcomes are harder to sustain than with perfect information.

To assess this hypothesis, we conducted a series of experiments in which a seller and a buyer are matched in pairs and repeatedly engage in the transaction of a good of heterogeneous quality that is structured as a *trust contract.* Higher quality is valuable to the buyer (principal), but costly to the seller (agent). In

[1] See Malcomson (2013) for a review.

[2] See (Cooper and Kagel, 2016) for a recent review of the evidence and relevance of social preferences.

the first stage of each transaction, the buyer pays a price upfront. In the second stage, the seller chooses the quality q of the good. Quality q is chosen from $\{1, ..., 10\}$, and the value of the good to the buyer is $10q$. The price p is chosen from $\{0, ..., 100\}$. Quality is not contractible.[3] There are two seller types, which differ in their cost of providing quality. For the high cost type, the absolute and marginal costs of providing positive quality are always larger. Each pair engaged in 15 transactions. We exogenously vary the reliability of the buyer's information about the seller's true costs: In the *hard information* treatments, costs are common knowledge, whereas in the *soft information* treatments, they are private information. However, at the beginning of the latter treatments, the seller can send a cheap talk cost signal to the buyer. Consequently, the buyer only knows the ex-ante probabilities of high or low costs and observes the non-verifiable cost signal.

We hypothesize that cooperation is more difficult to sustain with soft information, because the players cannot agree on what constitutes fair behavior. More specifically, consider the following intuitive reasoning:

(S1) When buyers believe that a seller has high costs, they are prepared to compensate quality increases with higher price increases.

(S2) Under soft information, buyers doubt that high-cost signals are truthful. They expect a temptation for low-cost sellers to signal high cost in the hope of benefiting from the buyers' willingness to compensate quality increases with higher price increases.

(S3) Thus, under soft information a buyer might compensate a seller who signals high cost less for higher quality than she would with hard information.

(S4) This can trigger a quality reduction by high-cost sellers: Even if they understand the informational constraints of the buyer, they may think they do not receive sufficient compensation for their quality.

If steps (S1)-(S4) hold, high cost relationships may be more difficult to sustain with soft information because mutual understanding about what constitutes a cooperative action in the relationship is harder to achieve. This reasoning is consistent with findings from the literature. First, it has been argued that mutual trust is crucial for upholding relationships (Zaheer and Venkatraman, 1995; Bachmann and Zaheer, 2006) – the absence of verifiable information may undermine such trust.

[3] Our experimental design closely follows the established gift-exchange paradigm (Fehr et al., 1997; Brown et al., 2004).

Second, evidence suggests that dishonest actions and attempts to gain unfair advantages through acts of cheating often meet with resistance and punishment (Brandts and Charness, 2003). In the soft information treatment, a trading partner may interpret high cost signals as such dishonest attempts by low-cost sellers, and she may therefore doubt their truthfulness. In turn, buyer and seller may have diverging views on what constitutes fair contractual terms and how the gains from trade should be distributed.

Third, Gibbons and Henderson (2012; 2013) recently put forward the argument that efficient relational contracts must "solve the twin problems of credibility and clarity". Clarity requires "not only a high level of task knowledge – i.e., of the actions that constitute cooperation, but also a great deal of relational knowledge – i.e., of the payoff to cooperation for each party, of each party's ability and incentive to defect, and of the actions and payoffs that constitute punishment." In the soft information treatment, the payoffs of the seller are private information. This reduction in relational knowledge makes coordination on what constitutes fair actions more difficult, which in turn may impede the formation of an efficient relational contract.[4]

To assess our hypothesis, we will focus only on high-cost seller pairs, for the following reasons. First, we expect high-cost sellers to unanimously signal high costs in the soft information treatment.[5] Hence, for this group, the cost signal does not differ between the treatments; the only difference is whether the signal is hard or soft.

Second, for high-cost seller pairs, the payoffs for every price-quality combination is identical across the hard and the soft information treatment. Consequently, only the buyer's beliefs about payoffs differs across treatments, but not the actual payoff for a given price-quality pair.

Finally, the treatment can only distort the buyer's belief in the direction of *higher* seller payoffs for a given price-quality combination, compared to the hard information treatment. This is the case because it is common knowledge that the payoff to the seller is *at the minimum* the payoff of a true high-cost seller. This is important from the pure credibility viewpoint: A specific price-quality pair that could be sustained in a relational contract with a high-cost seller under full information should also be sustainable in a relational contract with a high-

[4]Gibbons and Henderson primarily address standard infinitely repeated interactions and do not explicitly consider relational contracts supported by social preferences. Nonetheless, we believe that their clarity argument naturally extends to this situation and that asymmetric information is an important element in understanding the determinants of "clarity" in relational contracts.

[5]Which turned out to be true except for one seller.

cost seller under soft information, because the relationship generates the same profit for the buyer and at least the same profit for the seller, and this is common knowledge. Consequently, potential reductions in quality cannot stem from reductions in available rents, but must stem from belief driven disagreements about what constitutes fair behavior.

Turning to our data, we find that the average quality provided in high cost relationships is 5.4 under hard information, whereas it is 5.6 in the soft information treatments, contradicting the hypothesis that the introduction of asymmetric information reduces efficiency. To understand this finding better, we examine the data more closely.

First, we find that high-cost sellers receive a higher price for the same quality than low-cost sellers under hard information, which is consistent with (S1). Buyers are indeed willing to compensate sellers for higher costs, implying that the terms of trade depend on this information.

Second, consistent with (S2), the cost signal is not truthful in general, though it has some informational value: Almost without exception, the high-cost sellers state their type correctly. Two thirds of the low-cost sellers, however, also claim to have high costs. Moreover, the buyers' beliefs reveal that they anticipate this behavior, so that doubts about true seller types indeed exist following high cost signals. Thus, under soft information, buyers do not know the true cost type of sellers following high cost signals. Hence the fair compensation of a seller who signals high costs is ambiguous.

Indeed, when buyers observe a high cost signal in the soft information treatment, they indicate significantly higher desired quality for a given price in the first period, compared to the high cost hard information case. It hence appears that they desire altered contractual terms. Nonetheless, step (S3) does not hold: Despite the buyers' doubts and higher demanded quality, the empirical relationship between price and quality in high cost relationships under hard and soft information is not significantly different. This implies that buyers end up compensating sellers as if the cost signal was truthful, so that doubts about seller costs do not lead to lower prices for a given quality. In turn, the expected downward spiral for efficiency (S4) does not materialize. Pairs build and maintain relational contracts on the same terms as under hard high cost information.

Our data also shows that sellers capture 20-50% higher profits than buyers. One cause for this asymmetry might be that sellers move second in the transaction, and their quality choice effectively controls the distribution of rents. For the terms of the contract, it may therefore be decisive who moves second. In particular, the buyers may have been unable to translate doubts about the honesty of sellers into actions because they moved first.

To understand whether this hypothesis has merit, we conducted a second experiment in which we switched the order of moves within each stage game, and structured the transaction via a *bonus contract*. The seller moves first, chooses quality and indicates a desired price. The buyer then moves second and chooses a price. All other aspects of the experiment remain unchanged. The altered order of moves enables the buyer to determine the distribution of the gains from trade through the price choice, potentially enabling him to directly translate concerns about honesty into action.

This second experiment indeed reveals significant effects of the information structure on the terms of the relational contracts in high cost relationships. Under soft information, prices react less to quality, as buyers are not willing to compensate sellers as in the hard information benchmark, consistent with (S3). However, this reduction in compensation does not negatively affect the efficiency of the relationships. Sellers accept the altered terms under soft information and are willing to provide similar quality as under hard information, despite the reduction in compensation. Consequently, Step (S4) does not apply.

Interestingly, therefore, in both treatments the uninformed party contributes to the efficiency of the relationship by cooperating in spite of severe doubts about the trustworthiness of the informed player. This feature appears to be critical for the success of relationships under non-verifiable information.

Our paper contributes to the experimental literature on relational contracting by providing evidence on the formation of relational contracts with exogenous variation of the informational condition. Brown et al. (2004, 2012) study relationship formation in markets under complete information but with varying market power.[6] Extending the setup of Brown et al. (2004), Camerer and Linardi (2012) show that relationships are robust to stochastic hiring shocks. Renner and Tyran (2004) study buyer-seller relationships in markets for experience goods when temporary cost shocks change the terms of the implicit contract. They show that beneficial long-term relationships prevail in such settings, but are prone to price stickiness. Our paper differs from this literature by dealing with persistent asymmetric information about cost types in relational contracts.[7]

By studying asymmetric information in repeated gift exchange games, our

[6]Brown et al. (2004) show that bilateral long-term relationships in which rents are shared emerge endogenously in markets with excess supply of labor. In Brown et al. (2012), they show that these results extend to markets with excess demand for labor, but bilateral long-term relationships are less frequent.

[7]In unpublished ongoing work, Kartal et al. (2019) study the related but different question of how uncertainty about a player's patience affects the build-up of relational contracts.

paper also relates to the literature on asymmetric information in bargaining (for reviews, see Huck, 1999; Camerer, 2003). For instance, several authors have studied one-shot ultimatum games in which the proposer has private information about the pie size. Most of these papers show that responders give proposers the benefit of the doubt and are more likely to accept low offers (Mitzkewitz and Nagel, 1993; Straub and Murnighan, 1995; Croson, 1996). Our result that buyers take cost signals at face value under soft information in trust contracts is reminiscent of these findings. Ellingsen and Johannesson (2005) study a one-shot game in which sellers first make a sunk cost investment in producing a good, and then make a take-it-or-leave-it offer to a buyer who has a fixed and known valuation of the good. When the seller's investment costs are private information, high-cost sellers ask for lower prices and low-cost sellers ask for higher prices, anticipating altered buyer acceptance behavior. This relates to our result for the bonus contract treatments that high-cost sellers must accept lower prices under soft information.

The evidence presented in our paper also informs a growing theoretical literature analyzing repeated buyer-seller relationships with persistent hidden information, usually specified as principal-agent relations (Levin, 2003; Halac, 2012; Yang, 2013; Li and Matouschek, 2014; Malcomson, 2015). However,these papers focus on different questions than we do, such as: Under which circumstances can cooperative equilibria with high quality levels be sustained? How do the equilibrium dynamics look like? To which extent are the equilibria separating, that is, reveal the private information to the uninformed party?[8] By contrast, our set-up aims at testing the pure effect of reduced relational knowledge on the terms of relational contracts.

The remainder of the paper proceeds as follows: Section 2 describes the details of our experimental implementation. Section 3 derives hypotheses. Section

[8]Most importantly, contrary to our paper, the existing literature focuses mainly on cases where the efficient actions depend on types, so that efficiency requires separation. For non-persistent agent cost types, Levin (2003) shows that stationary contracts are optimal under general circumstances. Moreover, the optimal contracts with asymmetric information do not involve full type separation. Finally, no cost type exerts the first-best effort level. Contrary to Levin, Li and Matouschek (2014) suppose that the principal has (non-persistent) private information about the profitability of the firm. They show that bad states lead to conflicts that build up gradually, but are resolved immediately in good states. In a setting with persistent agent cost types drawn from a continuum, Malcomson (2015) shows that there are no fully separating perfect Bayesian equilibria satisfying standard refinements – this differs from our setting with discrete types. Halac (2012) focuses mainly on private information about the (constant) outside option of the principal. She shows that separating equilibria require a high prior probability of uncommitted types (with low outside options). She also discusses equilibrium dynamics, in particular, the speed of information revelation. Like Malcomson (2015), Yang (2013) considers agents with private cost information. However, he assumes that there are only two cost types.

4 presents our empirical results for trust contracts. In Section 5, we discuss bonus contracts. Section 6 concludes.

2 Experimental Design

Our experimental design modifies Brown et al. (2004) by considering fixed relationships and allowing for persistent asymmetric information. Subjects are randomly allocated as sellers or buyers. These roles and the relationships remain fixed for the whole experiment, with 15 transactions. In each transaction, the buyer of a good pays a price p and the seller provides this good with costly quality q. The stage game involves "trust contracts": The buyer moves first, paying the price and indicating a desired quality. The seller observes the price and the desired quality, and can then freely chooses quality. Thus, quality cannot be enforced.

We vary the buyer's information about the seller's cost type. In each session, it is common knowledge that 50 percent of the sellers will be randomly assigned to high and low cost types, respectively. Prior to the interaction, each seller learns his own type. In our hard information treatments, a buyer also learns the seller's true type before the interaction begins. In the soft information treatments, the seller holds private information about his type, and he can send the buyer a cheap talk signal about his type after learning it. The seller can select the signal independent of his true type, and the buyer knows this.

We speak of hard and soft rather than complete and incomplete information to focus on the verifiability of information. In the soft information treatment, the buyers receive information in the form of a signal (rather than no information at all), but it is not clear to which extent they trust it.

2.1 Parameters

In each transaction, the buyer chooses a price p from $[0, 100]$ and the seller selects a quality q from $\{1, 2, \ldots, 9, 10\}$. The desired quality q^d is chosen from the same set. For given choices of p and q within a round, a buyer's material payoff $\Pi_B(p, q)$ and the seller's material payoff $\Pi_S(p, q, \theta)$ are given by

$$\Pi_B(p, q) = 10 \cdot q - p \text{ and } \Pi_S(p, q, \theta) = p - c(q, \theta)$$

where $c(q, \theta)$ is the cost of quality q given cost type $\theta \in \{L, H\}$ as summarized in Table 1 below. Costs are strictly and marginal costs are weakly increasing in quality, for each cost type. For any $q > 1$, $c(q, L)$ is strictly lower than $c(q, H)$.

The difference between high and low costs, $c(q, H) - c(q, L)$, is increasing in q. Yet, since the marginal benefit of quality for a buyer always strictly exceeds the marginal cost, the efficient quality is 10 under both cost regimes.

In all treatments, and before the interaction took place, every seller is randomly assigned to type L or H and then privately informed about it. After observing their type, sellers in the soft information treatments choose between the message "I have low costs" and the message "I have high costs", irrespective of their actual type. Hence, sellers are free to either be honest or to lie about their type. A message can only be chosen at the beginning of the experiment and cannot be reversed later. A buyer receives the message selected by her seller and is informed that she will never obtain definite information about her seller's true costs. In the hard information treatments, a buyer receives either the message "Your seller has high costs" or the message "Your seller has low costs", depending on the true costs of her seller.

2.2 Procedures

At the beginning of the experiment, all subjects received written instructions and had to answer a series of control questions to ensure understanding. Once all subjects had answered their control questions, a summary of the experiment was read out aloud to guarantee common knowledge of the rules.

Assignment to the roles of buyers and seller as well as the matching of buyers and sellers are random, and each match persists for fifteen rounds. At the end of each period, both players receive a summary of their choices in the current round including the price and quality as well as the desired quality. Every subject is additionally informed about the own material payoff in the current round in terms of the experimental currency "Punkte" (points). The sum of payoffs, taken over all rounds, is converted into real money at the end of the experiment (10 points=1 CHF($1)) and paid out with the show up fee (10 CHF). In the soft information treatments, we additionally elicited buyers' first-order beliefs about the accuracy of the cost signal after the last interaction. We furthermore elicited sellers' second order beliefs about their buyers' first order beliefs.[9]

[9] We asked each buyer about all sellers' message choices, rather than about his actual seller. For instance, in a session with 16 sellers where 8 are assigned to low costs, we asked: "8 out of 16 sellers were assigned to low costs. How many of these sellers with true low costs sent the message 'I have low costs' to their buyers?". In a session with 16 sellers where 8 are assigned to low costs, sellers were asked: "Your buyer was asked the following question: '8 out of 16 sellers were assigned to low costs. How many of these sellers with true low costs sent the message 'I have low costs' to their buyers?' What do you believe: which answer did your buyer provide in response to this question?". Subjects earned an extra 20 points for each question if their stated belief was correct.

The experiment was computerized using the software z-tree (Fischbacher, 2007). For organizing and recruitment, we used the software hroot (Bock et al., 2014). Our subject pool consists primarily of students at the University of Zurich and the Swiss Federal Institute of Technology in Zurich. In total, 244 subjects participated in the experiment between Fall 2013 and Summer 2014. No subject participated in more than one session. On average, a session lasted 95 minutes with an average payment of 44.7 CHF ($ 45). An overview of the treatments and number of subjects and sessions is shown in Table 2.

3 Hypotheses

Our hard information treatment corresponds to a finite horizon game with complete information which has a unique subgame-perfect equilibrium with minimal qualities and prices in every period. Similarly, there are no perfect Bayesian equilibria with cooperation in the incomplete information game corresponding to the soft information treatment.

Previous repeated games experiments suggest, however, that some cooperation is likely to arise in both cases. One potential reason for cooperation in finitely repeated games is that some players display social preferences. For instance, it has been argued that fairness preferences can lead to cooperative outcomes even in finite-horizon games. In particular, it is straightforward to obtain equilibria with cooperation in a version of our game where players are privately informed about whether they have a "fair type", a type that always wants to split the surplus equally, rather than a "selfish type".[10]

To understand the potential impact of asymmetric information, we use the heuristic chain of reasoning presented in the introduction to argue that one might expect cooperation to break down in the incomplete information setting through an escalating chain of misunderstandings. Intuitively, disagreements about what constitutes the fair price can arise more easily than when the generated surplus is common information. If, due to the absence of common knowledge in the soft information treatment, the buyer and the seller lack a common understanding of what is fair, building and sustaining the relational contract becomes difficult. To illustrate this idea, suppose some sellers and buyers are fairness-minded, that is, committed to fifty-fifty surplus sharing, and both players regard a weighted average of the complete information fairness prices for high and low costs as adequate. However, the players' fairness perception is influenced by the information they possess. The buyers have imperfect information about the cost

[10]In other contexts, commitment types have been used for a long time (Kreps et al., 1982).

types. When announcing the first-period price, they can only do this based on their prior information and the signal they receive, which is not hard information. Whatever the price they choose, it will generate a higher surplus (and thus a higher share of the surplus) for a low-cost seller than for a high-cost seller. It therefore seems plausible that a fairness-minded buyer would start with a price that is between what she would give to a high-cost and low-cost seller in the complete information case.

Though sellers should take into account that the buyer does not know their type, it is not obvious to which extent they actually do this. It is at least conceivable that a seller who knows he has high costs regards a higher price as fair than a fair-minded buyer is prepared to pay when she is uncertain about the true costs. After a high cost signal, the buyer might therefore be expected to pay a slightly lower price than a high-cost seller considers adequate for the highest quality level. As the resulting quality of the seller does not quite satisfy the buyer, she responds with a slight price reduction. By iteration, a downward spiral of qualities and prices emerges, leading to our main hypothesis:

Hypothesis 1. *With soft information, the average quality in high cost relationships is lower than with hard information.*

In general terms, the above arguments suggest that incomplete information introduces ambiguity about what price is fair. The implied potential for a mismatch in fairness views between buyers and sellers can then lead to a breakdown of cooperation, as outlined in our steps (S1) - (S4) in the introduction.[11]

4 Results

In this section, we present our main results and relate them to the four steps (S1) - (S4) that we outlined in the introduction.

The two panels in Figure 1 show average quality over time for high and low cost relationships, conditional on whether cost information is hard or soft.[12] Because our hypothesis is derived for high cost relationships, we will mostly focus

[11] In Herz et al. (2016), we theoretically apply the idea of fairness types to our setting. Under complete information, efficient relational contracts can be sustained with fairness types. With asymmetric information, the buyer can no longer know with certainty which price is "fair" in the sense that it splits the surplus equally. We show that then the equilibrium predictions depend crucially on assumptions on how the buyers interpret the soft information they obtain from the seller and on the assessment of what constitutes fair behavior. We also show that even small disagreements of this kind can lead to an equilibrium where cooperation slowly breaks down.

[12] Here, we ignore the cost signal sent by the seller at the beginning. However, high-cost sellers are our main focus, and all but one high-cost seller indicated high costs.

on these. The left panel strongly suggests that the informational environment has no systematic effect on quality in high cost relationships. Average quality on high cost relationships under hard information is 5.4, and 5.6 under soft information. This difference is insignificant, using a t-test (p-value: 0.75).[13] This observation leads to our first result:

Result 1. *[The Effect of Information] In high cost relationships, the average quality is not significantly different with hard and soft information.*

Contrary to our hypothesis, introducing informational asymmetries seems to have no effect on the average quality in high-cost relationships.

Importantly, Result 1 does obviously not state that participants generally manage to coordinate on an efficient relationship: In spite of the massive efficiency gains from coordinating on a quality of 10, on average the parties fail to come close to an efficient outcome under either informational condition. Thus, the similar performance of hard and soft information relationships is not an immediate consequence of the large efficiency gains from cooperation (i.e., it is not a ceiling effect).

To understand where our four-step logic failed, we will consider each step in detail.

Step (S1) in our chain of reasoning suggests that, under hard information, high-cost sellers should receive more compensation for quality than their low cost counterparts. Our data confirms this intuition:

Result 2. *[Price-Quality Relationship] (i) There is a positive relation between average price and average quality for both cost types. (ii) Quality is significantly less sensitive to prices in low cost relationships than in high cost relationships.*

Evidence for this result is shown in Figure 2, which plots average prices and average qualities for every trading relationship conditional on costs. The quality-price relationship is positive for both cost structures, and it appears to be flatter for low cost relationships. Column (1) of Table 3 confirms this observation. In an OLS regression of average prices on average quality, a low cost dummy, as well as an interaction of the dummy with average quality, in the hard information treatment, we first see a large and significant coefficient of 7.7 on *Quality*, indicating that one unit of higher quality is compensated with a 7.7 points higher price in high cost relationships. Moreover, the coefficient on the interaction between quality and the low cost dummy is -1.5, implying that

[13] The t-test is conducted using the average quality provided in a trading relationship as one observation. Hence, there are 29 observations from hard information high cost relationships and 32 observations from soft information high cost relationships.

the slope of the price-quality relationship is significantly flatter under low costs ($p < 0.01$).

Do buyers doubt whether signals are true? Table 4 shows the relative frequency of high cost signals, conditional on true costs. High-cost sellers almost unanimously indicate high costs, as do roughly two thirds of the low-cost sellers. Further, the table shows that the buyers on average believed that 71% of low-cost sellers would signal high costs, which is not significantly different from the actual frequency ($p = 0.53$, t-test) as indicated by the first order beliefs.

We elicited beliefs ex-post (at the end of the experiment) to avoid any influence of belief elicitation on behavior. To address the converse concern that buyer experience may shape the stated beliefs, we also elicited the beliefs of third parties about the frequency of high cost signals in a separate experiment. These neutral observers on average believed in a frequency of high costs signals of 61%, which is again not significantly different from the actual frequency ($p = 0.26$).[14] Moreover, sellers believed that buyers believed that low-cost sellers would indicate high costs in 63% of the cases, roughly the actual empirical frequency ($p = 0.76$, t-test).

Hence, the empirical frequency of high cost signals by low-cost sellers coincides with the beliefs of buyers, sellers and neutral observers.[15] Consistent with step (S2), the belief data therefore implies that buyers had (justified) doubts about the cost type of sellers when observing a high signal: Given the better compensation of higher quality with higher costs, low-cost sellers may have an incentive to signal high costs.

Moreover, when buyers are confronted with a high cost signal in the first period, they translate these doubts into action. They ask for higher quality increases in response to any price increase than buyers in the hard information treatment who are matched with high-cost sellers. This follows from column (1) of Table 5, which shows results from a Tobit regression of desired quality on a hard information treatment dummy, interacted with the price paid up front.[16] In

[14] 31 subjects participated in the neutral observer experiment. They were given the original instructions of the soft information treatment and answered the same control questions as the participants. Then they were asked to guess the actual frequency of low-cost sellers sending a high cost signal as well as the frequency of high-cost sellers sending a high cost signal and were rewarded based on a quadratic scoring rule. The payment for both cases was determined according to the following formula: $R = 10 - 0.05 * (x - \overline{x})^2$. Consequently, a correct answer was rewarded with 10 Swiss Francs (approx. USD 10). Average earnings were CHF 27, including a CHF 10 show-up fee.

[15] For the more obvious case of high-cost sellers, it was generally expected that they truthfully signal high costs, which is also what is empirically observed (buyers believed that 94% would signal high costs. The neutral observers believed that 91% would signal high costs. The median and modal answer in both cases was 100%).

[16] We use Tobit regressions for all our regression analyses of chosen quality levels to account

column (1), we focus on the first period. As there has been no previous interaction, but the buyer already received the cost signal, the first period provides the cleanest indication for the quality that buyers consider appropriate for the price paid by them. Here, we include all buyers who observed a high cost signal in the regression, independent of their sellers' true costs. From the hard information treatment, only high cost relationships are included.

Column (1) shows that, for 10 additional points paid up front to the seller, buyers demand .64 units of quality less when they know for sure that the seller has high costs, compared to the case in which they received the non-verifiable high cost signal. This interaction is marginally significant at the 10% level.

However, contrary to our conjecture in Step (S3), the buyers' doubts about the sellers' costs did not translate into lower prices for a given quality: Column (2) of Table 3 shows OLS regressions on average prices within a trading relationship on the average quality provided within a relationship, controlling for the different treatments and taking into account cost signals. HL is a dummy for relationships with hard information and low cost. SH stands for relationships with soft information and high cost, independent of the cost signal.[17] SLL and SLH are dummies for relationships with soft information and low cost, with low and high signal, respectively. The baseline category consists of high cost relationships under hard information.

The highly significant coefficient on average quality again captures the positive relation between quality and prices in high cost relationships under hard information. The interactions of our treatment and signal dummies with average quality are of particular interest, since they directly indicate whether the quality-price relationship is different from the baseline case with high costs and hard information. Indeed the quality-price relationship is significantly flatter in low cost hard information relationships and in relationships in the soft information treatment in which low-cost sellers indicated low costs. However, such a difference to the baseline neither arises for high cost relationships with soft information nor for low cost relationships with soft information in which the seller indicated high costs. This implies that the compensation of sellers who signal high costs with soft information is similar as for sellers with high costs under hard information. Moreover, the coefficient on the interaction for low-cost sellers who signal low costs with soft information is not significantly different from the coefficient on the interaction for actual low-cost sellers under hard information ($p = 0.88$). Thus, we obtain the following result.

for corner solutions, which appear frequently.

[17]This signal was high in all but one case.

Result 3. *[Quality-Price Relationships with soft information] In the trust contract games with soft information, buyers compensate sellers as if the cost signal was truthful.*

The result shows why soft information has no adverse effect on efficiency: Even though buyers doubt that high costs are truthful, they behave as if they were taking them at face value. This also becomes evident in column (2) of Table 5, where observations from all periods are considered. The sizeable and significant negative interaction between hard information and paid prices from Period 1 essentially disappears when all periods are considered. Consequently, buyers appear to accept similar terms as in the hard information case. This behavior helps to maintain the same efficiency levels as under hard information.

At first sight, Result 3 seems to suggest that low-cost sellers profit from signalling high costs with soft information, as it enables them to obtain higher prices for a given quality. However, the evidence does not support this conjecture, because costs affect quality as well as prices: Low cost relationships with high cost signals are less efficient than low cost relationships with low cost signals.[18] Table 6 provides evidence for this finding. It shows results from an OLS regression of average quality on dummy variables for different combinations of true costs and cost signals.[19]

Relationships in which the seller sent a low cost signal under incomplete information are more efficient than high cost relationships under hard ($p < 0.05$) and under soft information ($p = 0.058$). Low cost relationships in which a high signal was sent, however, are not significantly more efficient than actual high cost relationships, and they are also less efficient than low cost relationships in which a low cost signal was sent, although the latter difference is not significant ($p = 0.11$). There are two potential explanations for these patterns in the low-cost relationship data. First, players under soft information might behave as if the cost signal was truthful, which would explain why relationships with soft information conditional on the cost signal so closely mirror their hard information counterparts. Second, instead the cost signal might not have an efficiency effect, and the quality differences might simply reflect selection of specific seller types with different abilities to maintain efficient relationships based on the cost signal.[20]

[18]There is also a significant difference in efficiency when comparing low cost and high cost relationships under complete information. Here, the difference in average quality amounts to 1.35 points ($p = 0.03$, Mann-Whitney test).

[19]The analysis of the impact of cost signals should not be understood as causal, since cost signals are endogenous to individual characteristics, and hence selection may take place conditional on the signal. Nevertheless, the associations in the data are interesting.

[20]These hypotheses could be analysed in future experiments. For example, one could conduct

While we have already seen that efficiency in high cost relationships is unaffected by information, we see that the terms of the relational contract have changed and that buyers and sellers coordinate on different quality-price relationships with soft information, resulting in differences in distributional outcomes. From Figure 2, we see that prices are generally higher than the equal split price, indicated by the solid lines. Thus, sellers get a disproportionately large share of the surplus: Table 7 summarizes the average profits earned by buyers and sellers across the different treatments.

Table 7 confirms the pattern already visible in Figure 2. Sellers capture significantly larger rents than buyers, except in low cost relationships with soft information in which low costs were signalled. The largest payoff difference materializes in low cost relationships with soft information in which high costs were signalled. However, somewhat surprisingly, the table also reveals that low-cost sellers who signal high rather than low cost are not better off than those who signal truthfully. The fact that relationships on average feature a lower quality following a high cost signal fully makes up for the higher prices conditional on quality, so that sellers' payoffs under complete and soft information are about the same. The efficiency loss relative to complete information low cost relationships is fully borne by the buyers, who make significantly smaller profits when the seller signals high rather than low costs.[21]

One potential reason for the high payoff share of the sellers might be that they move second and therefore control the distribution of rents. This suggests that the order of moves may play an important role in selecting the terms of the contract. We now deal with this point in detail.

5 Bonus Contracts

Since our hypothesis on possible adverse effects of asymmetric information on the performance of relational contracts relates to uncertainty about rent distribution, the uninformed party may require power over the distribution of rents within a

a within-subject design in which subjects participate in both a complete and the soft information treatment. This would allow to test the hypothesis that those sellers who are involved in less efficient relationships under hard information are more likely to signal high costs with soft information. Another possibility would be to conduct a treatment in which the cost signal is random. If there is a treatment effect related to the high cost signal in the latter case, selection cannot be the explanation. Since these questions are not the main focus of this paper, we leave these suggestions for future research.

[21] Again, this is an association and not a causal relationship. It could be the consequence of selection, as discussed before. Considering low cost relationships independent of the cost signal, buyers on average earn 4 points less per period with soft information than under hard information, but this difference is not statistically significant ($p = 0.15$).

transaction to translate its uncertainty into meaningful action. To test the role of second-mover control over rents, we conducted another experiment in which the buyer moves second and therefore directly controls the distribution of rents through his action.

5.1 Experimental Design: The Bonus Contract Game

We carried out eight sessions of a "bonus contract game", which is similar to the trust contract game, except that the order of moves within the stage game is reversed. In every period, the seller moves first, chooses quality and incurs the associated cost. In addition, she indicates a desired price. After observing these choices, the buyer sets the transaction price. Thus, again neither quality nor price is contractible.

As before, the stage game is repeated for 15 periods. We conducted 4 sessions with hard information and 4 sessions with asymmetric information. As in the trust contract games, information concerns the cost type of the seller ("high" or "low"). In the hard information treatments, the seller's cost type was common knowledge, whereas in the soft information treatments, the seller could send a non-verifiable cost signal.[22] In total, 252 subjects participated in the additional experiments. No subject participated in more than one session, and no subject had previously participated in the trust contract treatments. On average, a session lasted 95 minutes with an average payment of 52 CHF ($ 52).

5.2 Results

Figure 3 shows average quality in low and high cost bonus contract relationships during the 15 periods under hard and soft cost information. Again, we assess our main hypothesis by only considering high cost relationships, in which credibility is not reduced by soft information. Average quality in hard and soft information treatments is similar, 7.39 and 7.07, respectively. The difference is not statistically significant ($p = 0.51$, Mann-Whitney Test). Therefore, as in the trust contract experiments, the lack of payoff clarity does not appear to have a negative impact on efficiency in relational contracts.

Table 8 analyses the determinants of quality using OLS regressions, containing observations from both the trust contract and the bonus contract experiments. Column (1) shows coefficients of a regression of average quality within a relationship in high cost relationships on treatment dummies and relevant in-

[22]Again, the experiment was computerized using the software z-tree (Fischbacher, 2007). For organizing and recruitment, we used the software hroot (Bock et al., 2014).

teractions. If, as hypothesized, the second mover advantage affects quality, the bonus treatment dummy and the soft information treatment dummy should interact negatively. Column (1) confirms that this interaction is indeed negative and roughly equal to 0.53 quality points. This suggests that moving from the trust contract to the bonus contract, an efficiency-reducing effect of soft information may be present, but the interaction is not significant. Consequently, we cannot reject the hypothesis that soft information does not reduce efficiency, no matter who controls rent distribution in the stage game.[23]

Result 4. *[Verifiability of Information and Bargaining Power] The efficiency of relational contracts does not differ significantly with hard and soft information, independent of who controls the rent distribution in the stage game.*

Table 8 provides a further interesting insight that is independent of the informational condition: The coefficient on the bonus contract dummy in Columns (1) and (2) in Table 8 reveals that bonus contract relationships outperform trust contract relationships (even though statistical significance for low cost relationships is weak, probably due to a ceiling effect).[24]

Turning back to the impact of the verifiability of information on efficiency, we again analyse Steps (S1)-(S4) in detail and assess which of these do not apply. To this end, Figure 4 shows a scatter plot of the average quality and price in each hard information bonus contract relationship over the course of the 15 periods. The solid lines depict the price that would lead to an equal split of the rent, given average quality.

As in the trust contract case, higher quality is rewarded with higher prices, and sellers with higher costs are rewarded with higher prices for a given quality than low-cost sellers. This can be seen in Table 9, which shows results from an OLS regression on average prices. The coefficient on *averagequality* shows the significant and positive relationship between average prices and average quality in high cost relationships under hard information. The coefficient on the interaction between hard information low costs and average quality is significantly negative, indicating that the quality-price relationship is significantly flatter for low cost relationships with hard information, consistent with (S1).

Moreover, similar to the trust contract games, all high-cost sellers and 77.4% of the low-cost sellers signal high costs in the bonus contract games. First and

[23]Column (2) in Table 8 shows that information does not have a significant impact on average quality in low cost relationships either, even though the cost signals are not all truthful.

[24]Similar observations have been made in comparisons of one-shot trust and bonus games, the latter usually outperforming the former (see Fehr and Schmidt (2004) and Fehr et al. (2007)).

second order beliefs are again well aligned with these numbers.[25] Thus, buyers have significant (and justified) doubts about true costs when they observe a high cost signal, consistent with (S2).

Further, we argued that buyers might change their behavior in the bonus contract game because they control the distribution of rents in the stage game. First, as conjectured, Figure 4 shows that the second mover controls the rent distribution in the stage game: Quite strikingly, almost all observations are now to the right of the equal rent split line. This implies that, on average, the seller receives a lower price than the rent splitting price, and the buyers consequently receive a larger share of the rents.

But do they use this additional control to translate their doubts in the soft information treatment into lower prices? In Table 9, we see that the quality-price relationship changes significantly when information is incomplete. In actual high cost relationships, buyers on average receive .87 points less compensation for a one point increase in average quality than with hard information, and this difference is significant ($p < 0.01$).[26] Therefore, the verifiability of information has a clear effect on the quality-price relationship in the bonus contract games. High-cost sellers have to accept a lower compensation for the same quality with soft information than with hard information. The buyers' doubts about the truthful revelation of high costs translate into lower prices for a given quality.[27]

Result 5. *[Quality-Price Relationships under Soft Information] In bonus contract games, sellers indicating high costs under soft information get paid significantly less for the same quality than under high information.*

All told, (S1)-(S3) hold: When buyers know that costs are low, they provide less compensation for quality than when they are high. This gives low-cost

[25] Buyers on average believe that 69% of low-cost sellers would signal high costs. Sellers second order belief about this belief is 68%. These beliefs are not significantly different from the actual frequency ($p = 0.28$ and $p = 0.23$, respectively; t-tests).

[26] Moreover, the slope of the quality-price relationship is 2.5 points smaller in relationships with low-cost sellers that signalled high costs compared to hard information high cost relationships. Further, there is no difference in the quality-price relationship for low-cost sellers with soft information conditional on the signal ($p = 0.39$). Finally, for low cost relationships with high cost signals, the quality-price relationship is also not significantly different ($p = 0.92$) from the one of high cost relationships under incomplete information.

[27] In the bonus contract treatments, sellers had the possibility to signal a desired price after they provided the quality up front. In a tobit regression of desired prices on provided quality levels interacted with the information treatment, we find that, in the first period, sellers who signalled high costs desire prices that are even 6.4% larger than the prices desired by high-cost sellers with hard information. This difference is, however, not significant. Also when all periods are considered, desired prices are no different between the hard and soft information treatments. Hence, sellers would like the buyer to treat the cost signal as truthful. However, as our analysis has shown, they fail to achieve this goal.

sellers an incentive to mimic high-cost buyers, which leads to doubts of the buyers regarding the truthfulness of high cost signals. As expected, they are therefore less willing to compensate high-cost sellers for quality increases.

The fact that these lower prices did not result in lower average quality means that the final step (S4) in our reasoning is not borne out empirically: Sellers accepted the lower prices without in turn lowering their quality provision. Relationships coordinated on a different quality-price pair than with hard information. It appears that sellers understood the doubts of the buyers and their price reaction, and therefore did not react to the lower prices by reducing quality. Consequently, efficiency was unaffected.

The differences in control over rent distribution translate into considerable profit differences. Table 10 summarizes profits in the bonus contract games. Non-verifiability of information does not harm buyers in high cost relationships. To the contrary, their profits are significantly higher with soft information. This reflects lower prices for a given quality in the soft information treatment, and the fact that these lower prices did not lead to reduced quality. The increase in buyer profits therefore corresponds almost one-to-one to a reduction in seller profits, whose profits significantly decrease with soft information.

Further, we again observe that low-cost sellers barely benefit from signalling high costs. This result also reflects the lower quality-sensitivity of prices with soft information. Since buyers who received a high cost signal are not willing to pay a considerable premium for a given quality, sellers do not benefit from signalling incorrect costs.

6 Conclusion

This paper has analyzed the effects of asymmetric information about seller costs on the efficiency and rent distribution in experimental trading relationships. If sellers have private information about their costs, a majority of those with low costs signal high costs, presumably in the expectation of gaining an income advantage. As expected, buyers have strong doubts about the truthfulness of these signals.

However, when the stage game is structured as a trust contract game in which the buyer pays a price up front and the seller provides quality subsequently, this lack of clarity about actual costs does not translate into any differences in behavior. Despite their doubts about the truthfulness of the cost signal, buyers compensate quality as if the cost signal was truthful. In turn, trading relationships in which high costs are signalled are equivalent in terms of average quality and average prices to full information high cost relationships.

By contrast, in the bonus contract setting where the buyer moves second, uncertainty about sellers' costs does affect outcomes. Buyers are less willing to compensate sellers for supposedly high costs. However, true high-cost sellers accept lower prices in the soft information treatment. Consequently, the reduced compensation of quality does again not translate into reduced efficiency in the relationship. It does, however, lead to less compensation of higher quality by higher prices and thus to effects on the distribution of rents within the relationship.

Our results also have important implications for managing customer and labor relationships. Kahneman et al. (1986) provide survey evidence that community standards of fairness constrain the ability of firms to raise prices or cut wages in response to supply or demand shocks. Herz et al. (2018) have experimentally shown that past experience and observation shape which prices customers perceive as fair. In contrast, this paper suggests that negative reactions to (potentially excessive) price demands are subdued if buyers retain some positive belief that the seller is not acting in a dishonest and selfish fashion. Consequently, if firms can exploit an informational advantage, they may gain some leeway in price and wage setting without fairness concerns constraining their actions.

Given the complexity of the relation between asymmetric information and the efficiency of relations, our experimental analysis is only a first step, and our results may crucially depend on a variety of design choices. For instance, alternative parameterizations might lead to qualitatively different results. Potentially, conflicts could become more pronounced with soft information when the gains from cooperation are smaller than in the current setting. Moreover, our trading relationships remained fixed throughout the experiment. In that sense, our experiment was one-shot and subjects had no possibility to gain experience, in particular with different cost types which might be an important factor in driving a potential treatment effect. We believe that further exploring the determinants of the formation of efficient relational contracts under asymmetric information is a fruitful avenue for future research.

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Tables and Figures

Table 1: Cost of Quality

q	1	2	3	4	5	6	7	8	9	10
$c(q, L)$	0	0.5	1	2	4	6	8	10	13	16
$c(q, H)$	0	3	6	10	15	20	25	30	36	42

Table 2: Overview: Treatments, Sessions and Participants

Treatment	Number of Sessions	Total Number of Subjects
Trust Hard Information (TH)	4	116
Trust Soft Information (TS)	4	128

Table 3: Prices paid by treatment and cost signal

	(1)		(2)	
hard info - low cost (HL)	1.315		1.315	
	(3.285)		(3.308)	
Average Quality	7.686	***	7.686	***
	(0.318)		(0.320)	
HL X Average Quality	–1.538	***	–1.538	***
	(0.445)		(0.448)	
soft info - high cost (SH)			0.850	
			(2.614)	
soft info - low cost - low cost signal (SLL)			1.107	
			(4.122)	
soft info - low cost - high cost signal (SLH)			–1.038	
			(2.848)	
SH X Average Quality			–0.246	
			(0.407)	
SLL X Average Quality			–1.611	***
			(0.513)	
SLH X Average Quality			–0.500	
			(0.429)	
Constant	–1.761		–1.761	
	(2.184)		(2.200)	
Adj. R^2	0.929		0.942	
Observations	58		122	
Adj. R^2	0.929		0.942	
Observations	58		122	

OLS Regressions on average prices within a trading relationship over the 15 periods. One observation per trading relationship. "Average quality" is the average quality within a trading relationship over the 15 periods. Column (1) uses data from the hard information treatment only. Column (2) uses data from all trust contract treatments. Robust Standard Errors. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 4: Fraction of High Cost Signals with Soft Information

	Trust Contract
Overall	81.3 %
High-Cost Seller	96.9 %
Low-Cost Seller	65.6 %
1^{st} order beliefs (low-cost sellers)	71 %
2^{nd} order beliefs (low-cost sellers)	63 %
Neutral observer beliefs (low-cost sellers)	61 %

Table 5: Desired quality levels conditional on paid prices and information treatment

	(1)	(2)
hard information treatment	2.082	–0.710
	(1.607)	(1.398)
Paid price	0.127***	0.126***
	(0.016)	(0.013)
hard information*price	–0.064*	–0.008
	(0.037)	(0.028)
Constant	2.558***	3.950***
	(0.684)	(0.666)
Pseudo R^2	0.165	0.155
Observations	81	1215

Tobit Regressions on desired quality on observations for which high costs were common knowledge (hard info treatment) or high costs were signaled (soft info treatment). Lower limit: 1; upper limit: 10. Column (1) only contains observations from the first period. Column (2) contains observations from all periods. In column (2), standard errors are clustered at the relationship level (81 clusters)

Table 6: Regressions on average provided quality, accounting for the cost signal

	(1)	
hard info - low cost (HL)	1.345	**
	(0.677)	
soft info - high cost (SH)	0.206	
	(0.652)	
soft info - low cost - low cost signal (SLL)	1.898	**
	(0.920)	
soft info - low cost - high cost signal (SLH)	0.380	
	(0.723)	
Constant	5.405	***
	(0.494)	
Pseudo R^2	0.03	
Observations	122	

OLS regression on average provided quality within a trading relationship over the 15 periods. one observation per trading relationship. Robust standard errors in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 7: Average Profits by Treatment and Cost Signal

	Trust Contracts	
	Buyer	Seller
Hard Info - High Cost	14.27	20.88
Hard Info - Low Cost	26.44	32.24
Soft Info - High Cost	15.27	20.98
Soft Info - Low Cost	22.60	32.48
Soft Info - Low Cost - Low Cost Signal	29.32	31.93
Soft Info - Low Cost - High Cost Signal	19.08	31.34

Table 8: The Effect of Non-Verifiability of Information on Quality

	(1)		(2)	
	High Cost		Low Cost	
Soft Info	0.241		–0.442	
	(0.673)		(0.674)	
Bonus Contract	2.099	***	1.210	*
	(0.671)		(0.670)	
Bonus X Inc. Info	–0.604		0.684	
	(0.894)		(0.881)	
Constant	5.370	***	6.788	***
	(0.527)		(0.468)	
Pseudo R^2	0.03		0.02	
Observations	124		124	

OLS Regressions on average provided quality within a trading relationship over the 15 periods. One observation per trading relationship. Robust Standard Errors. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 9: Prices paid in Bonus Contract Relationships

	(1)	
hard info - low cost (HL)	–3.153	
	(3.415)	
soft info - high cost (SH)	1.912	
	(2.865)	
soft info - low cost - low cost signal (SLL)	10.065	
	(17.892)	
soft info - low cost - high cost signal (SLH)	–3.189	
	(6.139)	
Average Quality	8.211	***
	(0.240)	
HL X Average Quality	–1.060	***
	(0.394)	
SH X Average Quality	–0.867	**
	(0.391)	
SLL X Average Quality	–2.500	
	(1.866)	
SLH X Average Quality	–0.792	
	(0.767)	
Constant	–13.258	***
	(1.878)	
Adj. R^2	0.899	
Observations	126	

OLS Regressions on average prices within a trading relationship. One observation per trading relationship. "Average quality" is the average quality within a trading relationship over the 15 periods. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 10: Average Profits in the Bonus Contract Games

	Buyer	Seller
Hard Info - High Cost	26.48	18.81
Hard Info - Low Cost	38.48	27.85
Soft Info - High Cost	30.12	13.65
Soft Info - Low Cost	37.69	31.8
Soft Info - Low Cost - Low Cost Signal	40.2	33.53
Soft Info - Low Cost - High Cost Signal	36.96	33.39

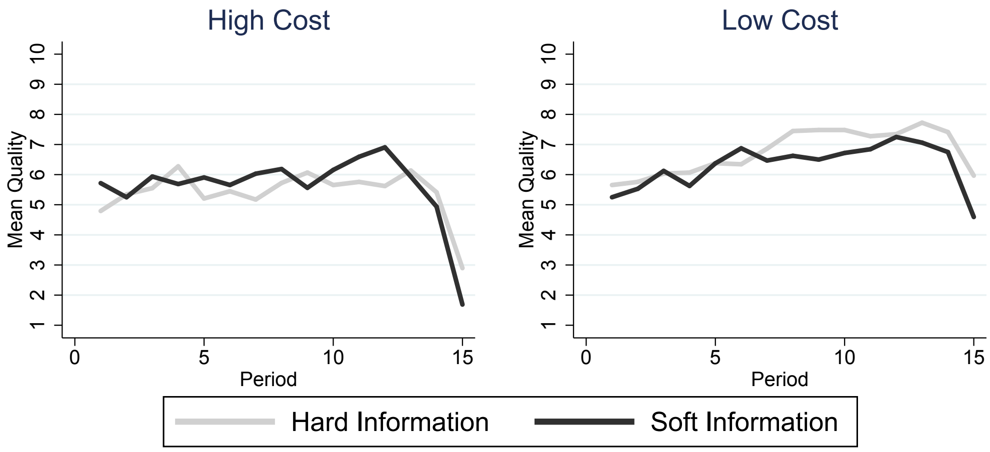

Figure 1: Quality over time in Trust Contract relationships. Left Panel: High Cost relationships under hard and soft information. Right Panel: Low Cost relationships under hard and soft information.

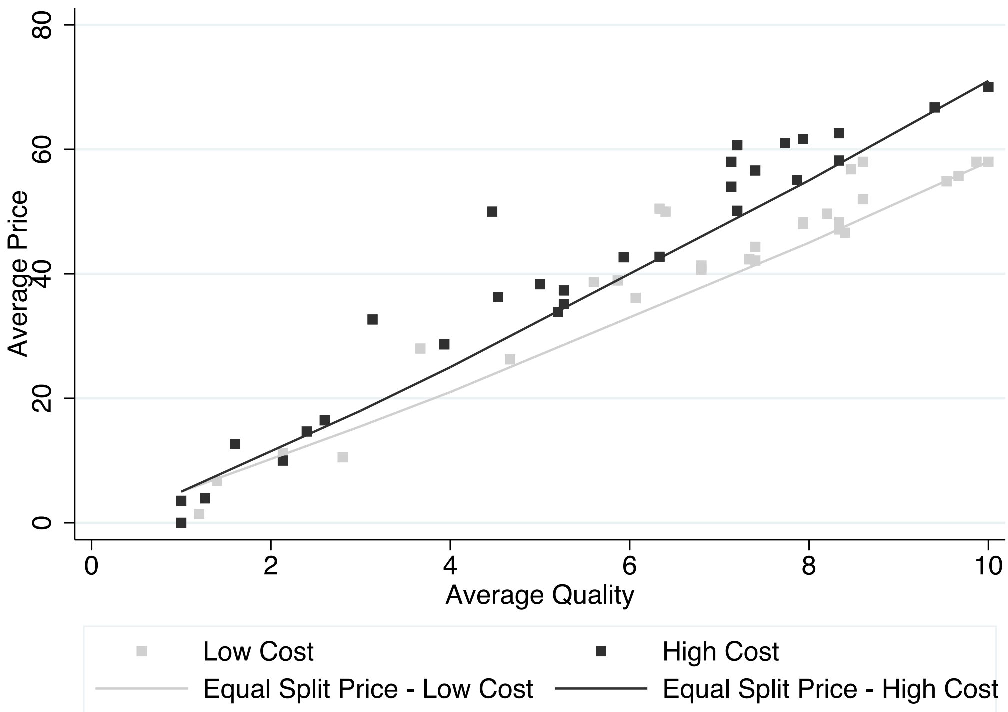

Figure 2: Association between price and quality. Each dot represents one relationship and depicts the average price and quality provided over the 15 periods in the relationship.

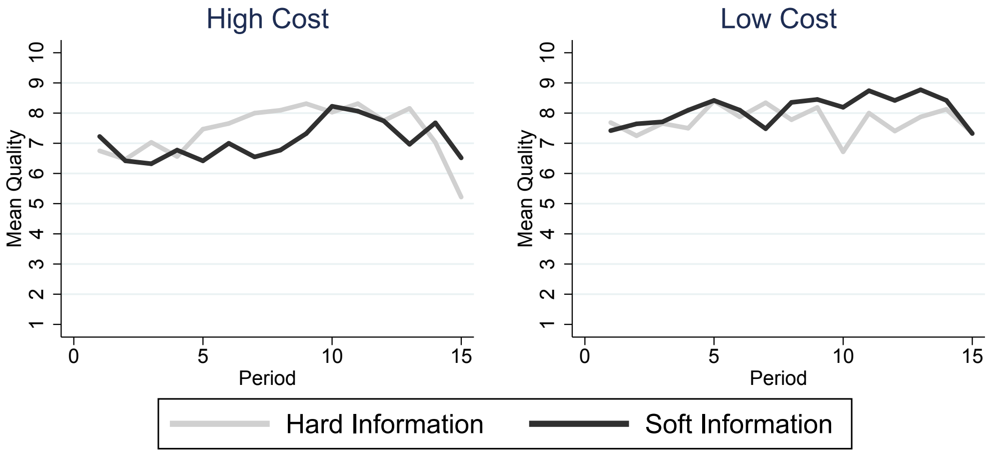

Figure 3: Quality over time in Bonus Contract relationships. Left Panel: High Cost relationships under hard and soft information. Right Panel: Low Cost relationships under hard and soft information.

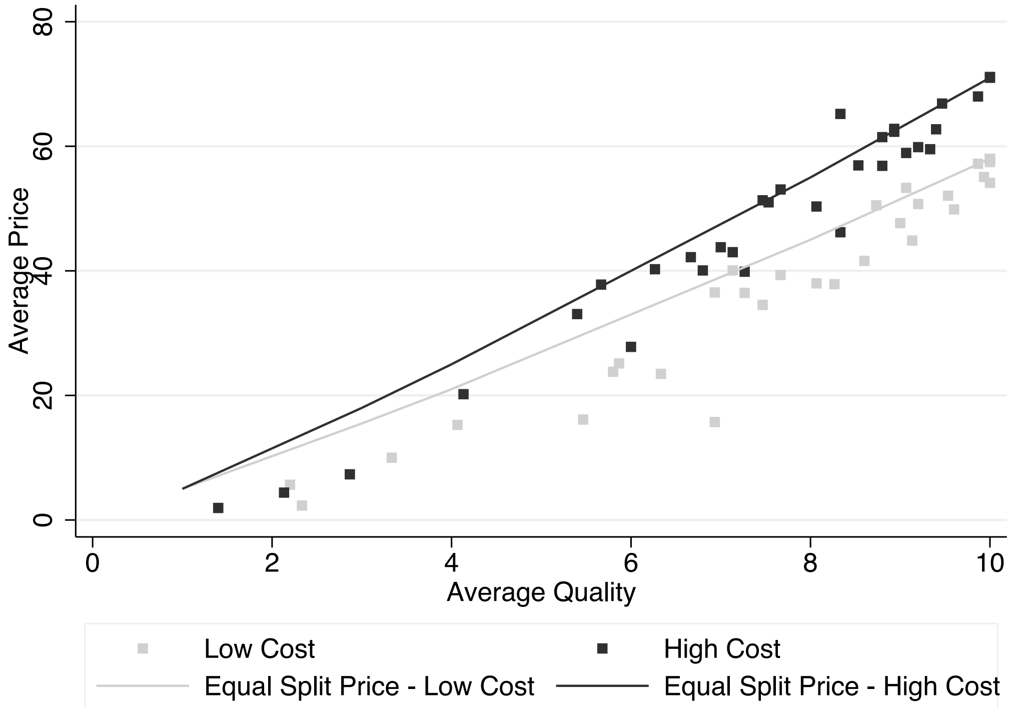

Figure 4: Association between price and quality in bonus contract relationships. Each dot represents one relationship and depicts the average price and quality provided over the 15 periods in the relationship.