Relational Contracting in Agricultural Supply Chain: Evidence from China's Wholesale Vegetable Markets

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Abstract

Purpose - Trading relationships based on informal agreements (relational contracts) remain an important mechanism in organizing agricultural supply chains. Relational contracts coordinate buying and selling, and provide the trading parties with demand and supply assurance without losing flexibility in pricing and delivery arrangements. Understanding the functioning of these relationships is important. This paper makes one of the first empirical analyses of these supply chain relationships using a proprietary dataset that records every single transaction in a large wholesale vegetable market in China.
Design/methodology/approach - Literature on relational contracts and agricultural supply chain relationships was reviewed and testable hypotheses were distilled and adapted to a conceptual framework. Relational practices were measured systematically in the vegetable transaction data. Econometric models were then employed to test the hypotheses.
Findings - Trading relationships prove to be important in determining transaction prices, and could explain, to a significant, the observed price dispersion in the market. Specifically, this analysis finds that relational buyers in general are paying a price premium; traders absorb part of the price risk for their contractual partner when supply makes large swings; the value of a relationship changes as it evolves.
Originality - Empirical evidence regarding relational contracts is rare, especially quantitative evidence. Trading relationships in agricultural supply chains have been understudied. The findings of this study will shed light on the organization of agricultural supply chains in China and elsewhere, and lay a foundation for the formulation of agricultural market regulations.

Keywords Agricultural supply chains, Trading relationships, Relational Contracts, Wholesale markets, China
Paper type Research Paper

1 Introduction

Many trading relationships for agricultural products are informal or relational. Informal agreements formed by trading partners, often called relational contracts (RC), are sustained via the value of future interactions (Baker, Gibbons and Murphy, 2002). Relational contracts coordinate buying and selling along the supply chain, provide the parties with demand and supply assurance without losing flexibility in pricing and delivery arrangements. RC are effective in environments where the institutions for verifying and enforcing formal contracts are incomplete. Individuals who repeatedly interact can sustain the trading relationship without any legally enforceable obligations if they place a sufficiently high value on future transactions.

In the context of agriculture, contracts have become an important mechanism in organizing modern agricultural markets. While there is a voluminous literature on agricultural contracts, researchers sometimes do not distinguish between formal, written contracts and informal agreements (Michler and Wu, 2019). Understanding the functioning of relational contracts is important for us to understand the organization of modern agricultural supply chains. Nevertheless, empirical evidence regarding the functioning of RC is rare, especially quantitative evidence. Most of the studies of agricultural contracts focus on contract farming, i.e., production contracts (e.g., Rao et al., AJAE 2012). Empirical analysis on informal supply chain relationships has been limited by the paucity of data – relational practices are, by definition, hard to codify, context-specific, and, therefore, hard to measure.

Access to a proprietary database allows me to make one of the first empirical analyses of RC and their impacts at an intermediate stage of agricultural supply chain. The database records information of every transaction in a large wholesale vegetable market in China. These proprietary data are held by the corporation managing the market and have not been previously used for economic research. The most important feature of the vegetable wholesaling data is that we can observe the identity of each trader in each transaction, through a market-specific trader ID. As in most wholesale produce markets in developing countries, seller prices are not posted and are negotiated by buyers and sellers during each transaction.

Preliminary analysis of the data reveals significant evidence of trading relationships – repeated transactions between the same trading parties. Consistent with the data, field interviews with traders at this market indicate that sellers and buyers establish trading relationships with each other and often tailor trading arrangements to the needs of their counterparties. These relationships are not governed by any written contracts enforceable by laws or regulations and thus must be "self-enforcing." While theoretical models share some common predictions, formal tests of these predictions are lacking. These trading relationships provide an excellent empirical context to study the dynamics of relational contracts, and to test hypotheses in the theoretical literature.

Further, this market represents a kind of economic paradox in the sense that, at first glance, one might conclude that it is a vigorously competitive markets: there are many buyers and sellers, frequent trades, relatively homogeneous products and there appears to be an adequate flow of market information. Yet empirical analysis reveals strong and persistent price dispersion for these homogeneous goods, a feature not reflective of a competitive market.

In this paper I link the stylized price dispersion to the existence of trading relationships. Economists have long suspected that relationships between agents might be important for us to understand price dynamics in various markets. Wilson (1980) finds that long-term bilateral exchange arrangements explain, to a large extent, the price dynamics in the New England fish market. Studies of financial markets (e.g., Di Maggio et al., 2017) show that trading relationships prove essential in explaining different pricing behavior. Going along this path, I set out to explain, using the theory of relational contracts, why a decentralized market where the central assumptions of perfect competition are present should exhibit a stable daily dispersion of prices.

The specific questions to answer are as follows. First, what causes the price variation? What is the difference between "relational trading" and "idiosyncratic trading"? Do buyers who trade with stable partners pay systematically different prices from others? Second, what are the incentives to formation of trading relationships? What is the value of trading relationships to buyers and sellers? Third, what are the strategies traders use to sustain relationships? What could potentially cause a relationships to break down?

The contribution of this paper will be threefold. First, it directly tests predictions from the relational contracting literature in the context of agricultural supply chain. Second, it systematically measures relational practices and confirms that the adoption of these practices plays a crucial role in the formation of transaction prices. Third and more fundamentally, it offers a new angle in explaining price dispersion in a seemingly competitive market. The findings not only shed light on the industrial organization of wholesale market for perishable products, but generate insights that may lead to further advances in the economic modelling of market evolution and pricing dynamics, well beyond the confines of a particular agricultural market.

The structure of this paper is organized as follows: Section 2 reviews briefly the related literature; Section 3 describes the empirical setting and the data; Section 4 sets up a conceptual framework and lists the hypotheses; Section 5 presents the empirical analysis; and Section 6 concludes.

2 Literature Review

The theoretical literature has developed a variety of models to capture the salient features of informal relationships. Pioneering works on relational contract theory include Telser (1980) and Klein and Leffler (1981), who show formally that short-term opportunistic behavior can be disciplined by inter-temporal incentives. Since then, major theoretical developments involved addressing the enforcement problems (e.g., MacLeod and Malcomson 1989; Baker, Gibbons and Murphy 1994, 2002), incorporating asymmetric information considerations (e.g., Levin 2003) and uncertainty over parties' commitment to the relationship (e.g., Halac, 2012).

Empirical studies that test the theories of relational contracts are relatively few. In the context of agriculture, evidence regarding the role of RC in agricultural supply chains is rare, especially quantitative evidence. Most of the studies involving relational contracts focus on contract farming, i.e., production contracts. These studies assess how RC impact farmer welfare (e.g., Michelson, 2013) and how contracts impact productivity and efficiency (e.g., Rao et al., 2012). One example that directly test the prediction regarding the value of contracting relationships is Beckmann and Boger (2004), who studied Poland hog production contracts in a setting where the costs of third-party enforcement are variable during political transition. Their results indicate that the enforceability of these production contracts is positively correlated with the value of the relationship.

I focus on the impact of trading relationships at the intermediate stage. Macchiavello and Morjaria (2015, 2019), Macchiavello and Miquel-Florensa (2018) are related empirical works that share with my study a developing-country setting. Macchiavello and Morjaria (2015) have used transaction-level data of the Kenyan rose export sector to show that, due to limited enforcement, the volume of trade is constrained by the value of the relationship. Macchiavello and Miquel-Florensa (2018) compare integrated firms and informal relationships between firms and how they adapt to shocks in the context of the Costa Rica coffee chain. There is strong evidence that these relationships provide demand assurance, although less than integration does, when there is weather-induced increases in supply. Macchiavello and Morjaria (2019) study relational contracts between upstream farmers and downstream mills in Rwanda's coffee industry. Their analysis indicates that increasing competition reduces the use of relational contracts and alters farmers' temptation to renege. Another related example is Antras and Foley (2015). Using data on trade contracts for an international poultry processor, the authors show that in the early stages of the relationship, the temptation for the customer to default is high. As the relationship ages, the continuation value of the contract increases and the processor is willing to execute more flexible financing terms. My empirical investigation of China's vegetable wholesaling industry could prove valuable to this literature by showing how informal relationships affect transaction prices and revealing the mechanisms at play.

Outside the specification of RC, the literature also offers theory predictions and empirical evidence of trading relationships. For example, Kranton (1996) proves in a structured model that agents can sustain cooperation by monotonically increasing the level of exchange within a relationship. Hendershott et al. (2019) find in the OTC corporate bond market that insurers engage in long-term repeat, but non-exclusive relations, and these relations are persistent from year to year.

Among these, a closely related strand of literature is the analysis of wholesale markets for fish (see Sapio, Kirman and Dosi (2011) for a detailed overview). For example, Weisbuch, Kirman and Herreiner (2000) assume buyers gain experience from previous transactions and learn their way to establish regular trading relationships. Their models predict two distinct types of buyer behavior – some buyers should be loyal, while others should keep on shopping around. Price dispersion is the outcome of this co-evolutionary process. None of these studies, however, adopt a relational contracting framework to explain pricing dynamics. My study not only extends these results to a different type of market but uses the implications of RC theory to explain the observed price patterns. I show that the pure price effect of trading relationships is large and quantify its magnitude.

3 The Market and the Data

3.1 The market

Knowledge of the market comes from field observations, interviews with market participants (traders and administrators) and local authorities. This market is one of the largest wholesale vegetable markets in China and draws from multiple production regions all over the country, depending on the time of year. The products include more than 80 types of commercially valuable vegetables, which vary over season. The market is open every day from early in the morning (usually 2 a.m.) to the afternoon. Prices are not posted. Sales are made using a "take-it-or-leave-it" pricing approach, generally. When a buyer wishes to buy a particular quantity, he asks a seller for the price. The seller quotes a price and the customer would usually either buy or walk away.

According to Gao (2019), one of the market managers interviewed, on most days the market clears or gets very close to clearing. In other words, most sellers are able to sell all of the products they brought to the market. Storage is possible for some products but not others, and largely depends upon weather conditions. Except for commodities storable at room temperature, such as potatoes and pumpkins, overnight storage is costly – sellers will have to rent a cold storage facility. For extremely perishable commodities, such as spinach, unsold inventory must be discarded at the end of the day. Therefore, sellers have incentives to discount prices as the trading day ends. Wang (2019), a seller specializing in cauliflower and broccoli, told me that relational customers are valuable to him in the sense that their orders will help him estimate the demand of the day. Although he cannot adjust the amount brought to the market, he could price strategically to reduce the risk of dump selling at the end of day.

There are fixed populations of registered sellers and buyers, but on each trading day, only a proportion of them come to the market. The sellers are wholesale vegetable-merchants who buy their merchandise from vegetable growers; the buyers are secondary wholesalers, retailers, and buyers for restaurants, institutions (hospitals, company canteens, schools) and supermarkets. Most sellers specialize in one vegetable within a given period of time. Buyers may sell in nearby cities or a market located far away, and usually buy a variety of vegetables.

Many regular traders have a long-term established business in this market. Sellers have to pay a yearly rent to reserve a stall at the market ($3,600/year), and buyers have to pay some administrative fee. Chen (2019) and Xiao (2019), two buyers who have been coming to this market since 2009, purchase a variety of 10-20 vegetables every time they come. They both sell to a smaller wholesale produce market in Tianjin (a city located 400 km away from the market). They claim that they have a go-to-seller for most of the commodities they purchase. "You can always find what you need at this market", said Chen (2019). "If my regular seller is not present, I simply buy from someone else. But this rarely happens and most times he will tell me in advance and I will coordinate my procurement schedule accordingly. However, I periodically search to avoid being exploited."

Prices in this market are transaction-specific in a three-fold sense. First, each individual seller sets his own prices. Second, each seller may have different prices for different buyers. Third, a seller may offer a different price to the same buyer at different times of the day. On each trading day after the market closes, the average price for each commodity will be posted online and is public.[1]

3.2 The data

The proprietary database is held by the company managing the market and has not been previously used for economic research. The database describes the daily transactions in the market. For each transaction we know the date and time, specified to the second, the identities of the buyer and seller (a market-specific trader ID) involved in the exchange, the product, the quantity and the price.

The company was only willing to give me limited access to the database. I chose cauliflower and Chinese cabbage for the purpose of this study for several reasons. First, they are two of the most widely consumed vegetables in China. Second, the top 5 commodities of this market (in trading volume) in 2018 are cauliflower, pumpkin, Chinese cabbage, green pepper and potato. Among these, pumpkin and potato are storable, which means inter-day arbitrage is possible. Green peppers are quite heterogeneous in size. The appearance of Chinese cabbage and cauliflower, on the other hand, are relatively homogeneous. In addition, while there is moderate demand seasonality for Chinese cabbage, there is, to my knowledge, none for cauliflower.

The final dataset at hand encompasses transactions from January 2016 to December 2019. There are 186,294 and 253,022 transactions concerning Chinese cabbage and cauliflower, respectively.

3.3 Descriptive statistics

Because some quotes may be misreported, leading to extreme estimates, for all analyses involving prices I trim the data by removing transactions of which prices lie below the 5th or above the 95th percentile of the price distribution on each trading day.

Figure 1 and 2 present the day-to-day fluctuation in market total trading volume and volume-weighted average price for the two vegetables. Total daily sales vary considerably

[1] The prices are available on the market's official website: www.sgvindex.com.

but follow a seasonal pattern. Price fluctuations are also predictable to a certain extent.

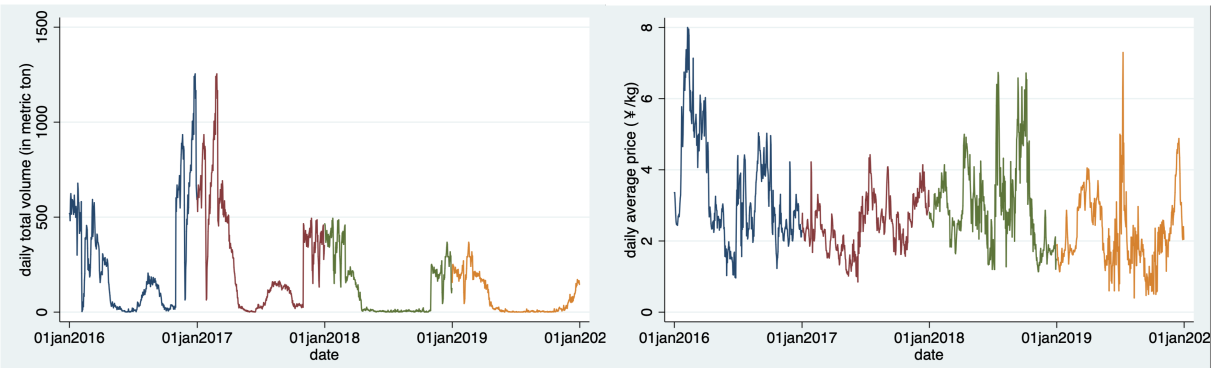

Figure 1: Daily trading volume & volume-weighted average price - cauliflower

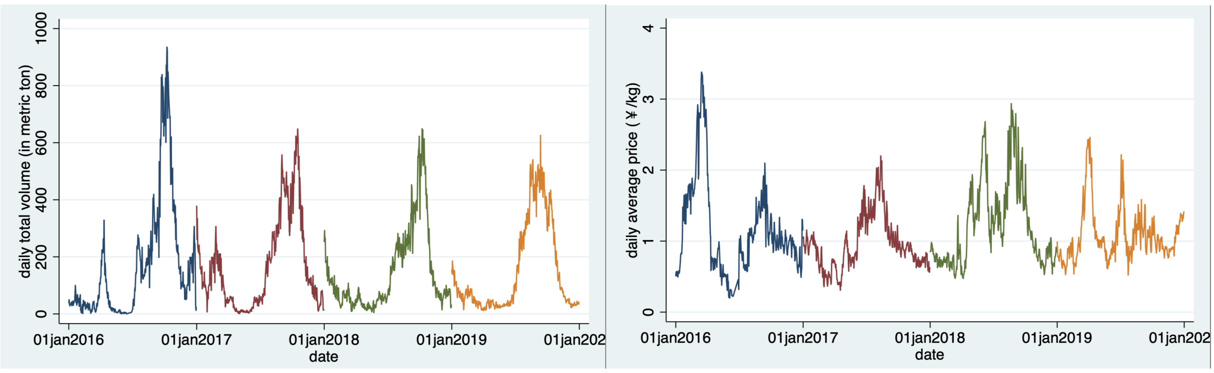

Figure 2: Daily trading volume & volume-weighted average price - Chinese cabbage

Price dispersion is wide and persistent on most days. Figure 3 below are high-low price charts to show the magnitude of price dispersion on some trading days.

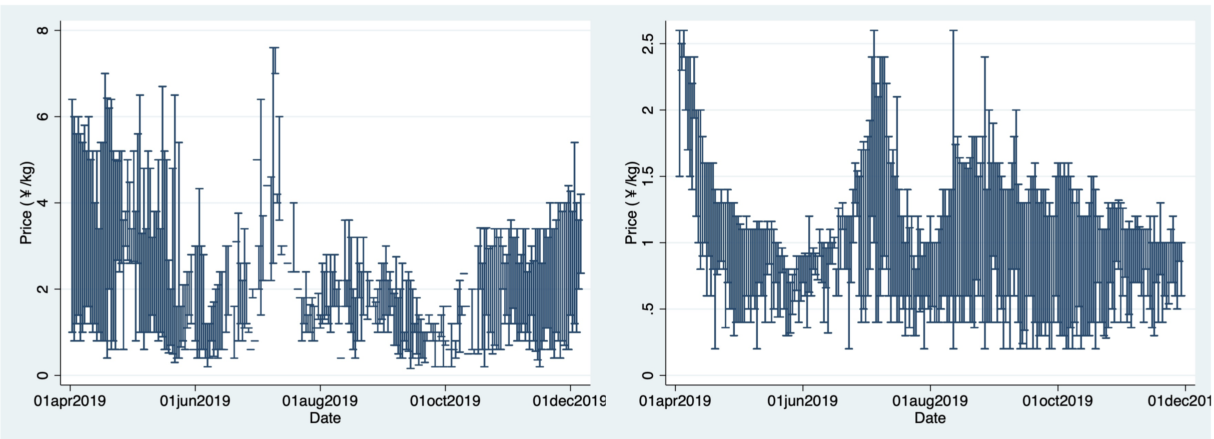

Figure 3: Evidence of daily price dispersion (left: cauliflower; right: Chinese cabbage)

While some of the price dispersion could potentially be attributed to product heterogeneity across sellers, why a single seller charges different prices on a given day remains unexplained. Figure 4 below depicts examples of price dispersion for two sellers.[2] The two figures on the left plot transaction price over transaction volume for all transactions a seller made on a single trading day. Transaction volume does not seem to play a role in determining transaction price. The two figures on the right indicate that there is no direct linkage between a seller's price quote and time of the transaction. In other words, "within" seller price dispersion cannot be solely attributed to the seller's inventory management strategy over the course of a day.

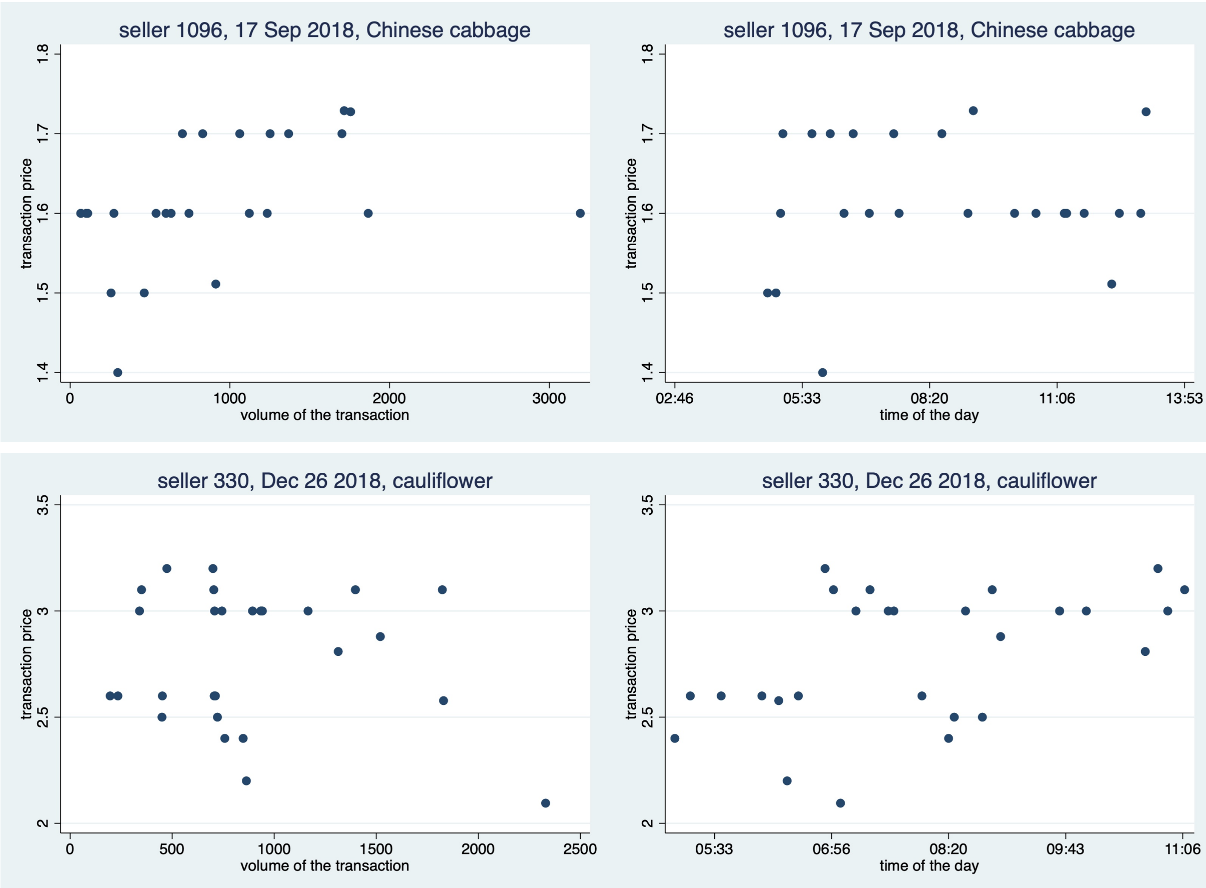

Figure 4: Examples of price dispersion "within" individual sellers

[2]These two sellers both came to the market for a significant amount of days in the data.

The number of buyers and sellers that come to the market fluctuates by season, while the ratio of the two groups stays relatively stable, as shown in figure 5.

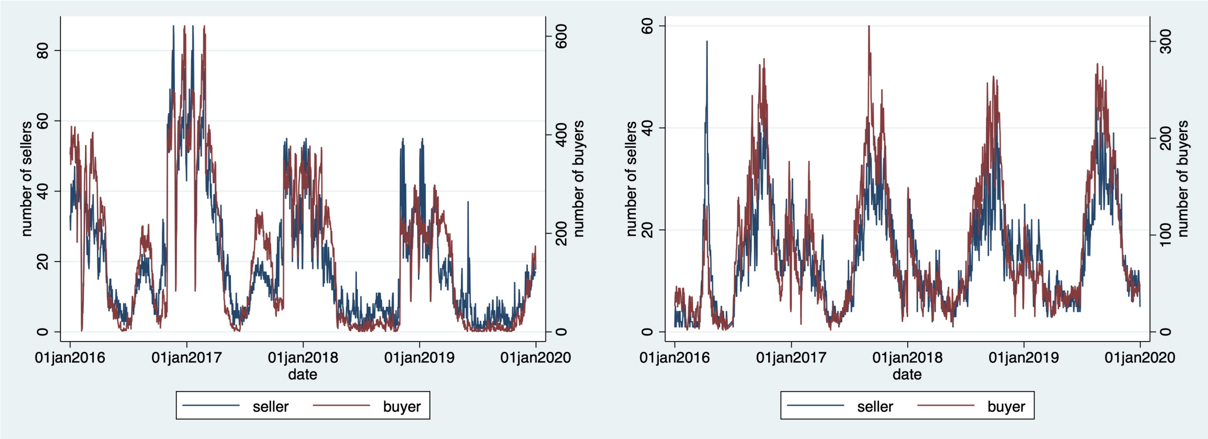

Figure 5: Daily number of buyers and sellers

Table 1 below reports descriptive statistics for the two vegetables at the trading day level.

Table 1: Summary statistics: trading day

	Cauliflower (Obs: 1339 days)				*Chinese cabbage (Obs: 1335 days)*			
Variable	Mean	Standard Dev.	Min.	Max.	Mean	Standard Dev.	Min.	Max.
Avg. price (¥/kg)	2.92	1.35	0.80	8.82	1.30	0.52	0.39	3.38
Number of transactions	149	150	1	635	127	97	2	391
Total trading volume (kg)	155,025	208,877	64	1,254,370	197,150	188,085	1,012	934,617
Avg. transaction size (kg)	557	213	64	4,077	1,045	570	147	16,271
Number of buyer	135	134	1	621	104	75	2	316
Number of sellers	18	15	1	87	16	10	1	47
Seller HHI	0.23	0.23	0.02	1	0.16	0.22	0.00	1
Buyer-Seller ratio	6.49	4.05	0.40	22.00	6.81	3.34	1.50	42.00

Table 2 reports descriptive statistics of trading activity of cauliflower traders. I distinguish those who, on average, come to the market to sell cauliflower more than 60 times a year from the rest of the sample and categorize them as regular traders.

Table 2: Summary statistics: trading activity (cauliflower)

Type	Variable	Mean	Standard Dev.	Min.	Max.
Panel A: Buyers					
All buyers (N=4611)	Number of days present per year	16	27	1	201
	Total purchase per year (metric ton)	136	196	2	2,287
	Avg. daily purchase (kg)	1,333	1,000	14	16,810
	Number of sellers traded with per year	23	15	1	78
	Avg. number of sellers per day	1.6	0.5	1.0	4.2
Regular buyers(N=456)	Number of days present per year	93	30	60	201
	Total purchase per year (metric ton)	288	261	4	2,287
	Avg. daily purchase (kg)	1,670	959	56	7,512
	Number of sellers traded with per year	37	16	2	78
	Avg. number of sellers per day	2.0	0.5	1.2	4.2
Panel B: Sellers					
All sellers (N=1604)	Number of days present per year	21	31	1	205
	Total sales per year (metric ton)	20,781	23,475	10	114,905
	Avg. daily sales	12,373	6,250	62	31,047
	Number of buyers traded with per year	258	158	3	687
	Avg. number of buyers per day	15.1	6.0	1.0	36.3
Regular sellers (N=65)	Number of days present per year	96	33	56	205
	Total sales per year (metric ton)	35,792	25,009	1,379	114,906
	Avg daily sales	18,747	9,366	658	112,365
	Number of buyers traded with per year	379	111	113	687
	Avg. number of buyers per day	20.9	6.2	4.8	36.8

On average, a buyer purchases from fewer than 2 sellers every time she comes to the market, while those who come more regularly buy from 2. An average seller sells to 15 buyers per day, while regular sellers sell to 21 on average.

3.4 Trading relationships

I define a relationship based on two criteria: (i) the buyer-seller pair trade at least 30 times within a year; (ii)"*trade/both-present ratio*" of that year ≥ 0.5. The ratio is calculated as the "*number of days the buyer and the seller trade*" divided by "*number of days the buyer and the seller are both present*". I denote it as "tp ratio" hereafter. By this definition, a relationship could breakdown and reconstitute. Any relationship that was not active in the previous year but reconstituted will be treated the same as a newly initiated relationship. This definition excludes relationships that trade irregularly, i.e., the tp ratio is high but the number of trades is low. One caveat regarding this definition is that it does not distinguish relationships between traders that conduct trade in a short time window versus those that trade occasionally throughout a year.

Figure 6 and figure 7 plot the tp ratio over "number of days both are present" and "number of days the buyer and the seller trade", respectively. Each dot is a buyer-seller pair. The yearly and monthly ratios are presented, along with the ratio of the whole period. The figures display the case of cauliflower. From figure 6 we can see that the likelihood of having a high ratio decreases as the number of days both the trading parties are at the market increases on a annual scale. If we look into one particular month, the ratio is distributed quite evenly over different visiting frequencies.

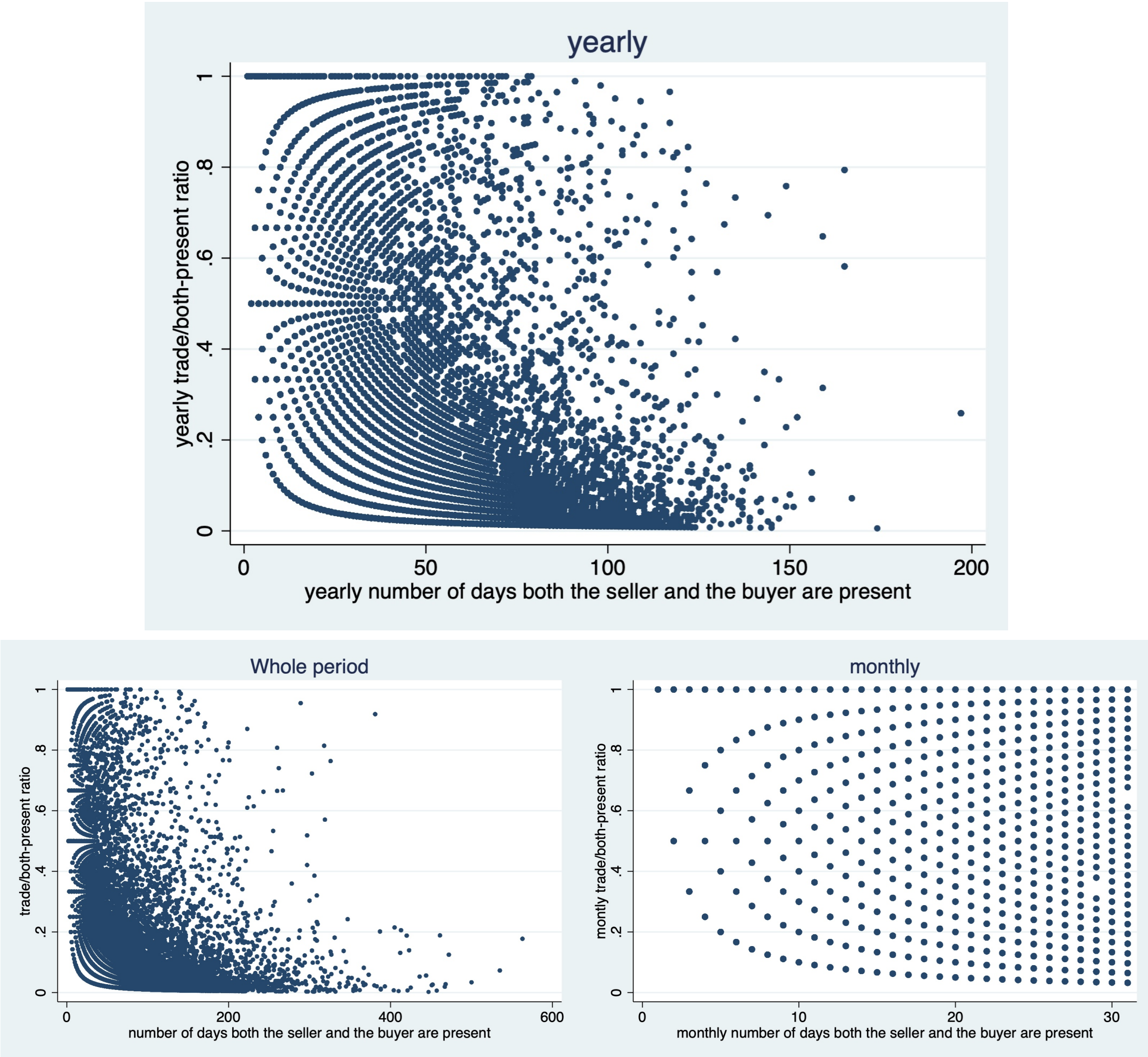

Figure 6: tp ratio versus number of days the buyer and seller are both present

The top panel of figure 7 plots the yearly ratio over the yearly number of trades. The pairs above the green line and to the right of the red line, by definition, have a trading relationship.

In total, 557 relationships for cauliflower and 431 for Chinese cabbage ever existed throughout the whole data period. Table 3 summarizes the characteristics of the relationships for cauliflower. The average relationship had 48 transactions per year, and traded 52,848 kg of cauliflower. The longest relationship lasted 1,199 days, while the average lasted for 228 days. The tp ratio ranged from 0.51 to 1, with the average being 0.77. Buyers on average had less than two relationships, while sellers had more than eight.

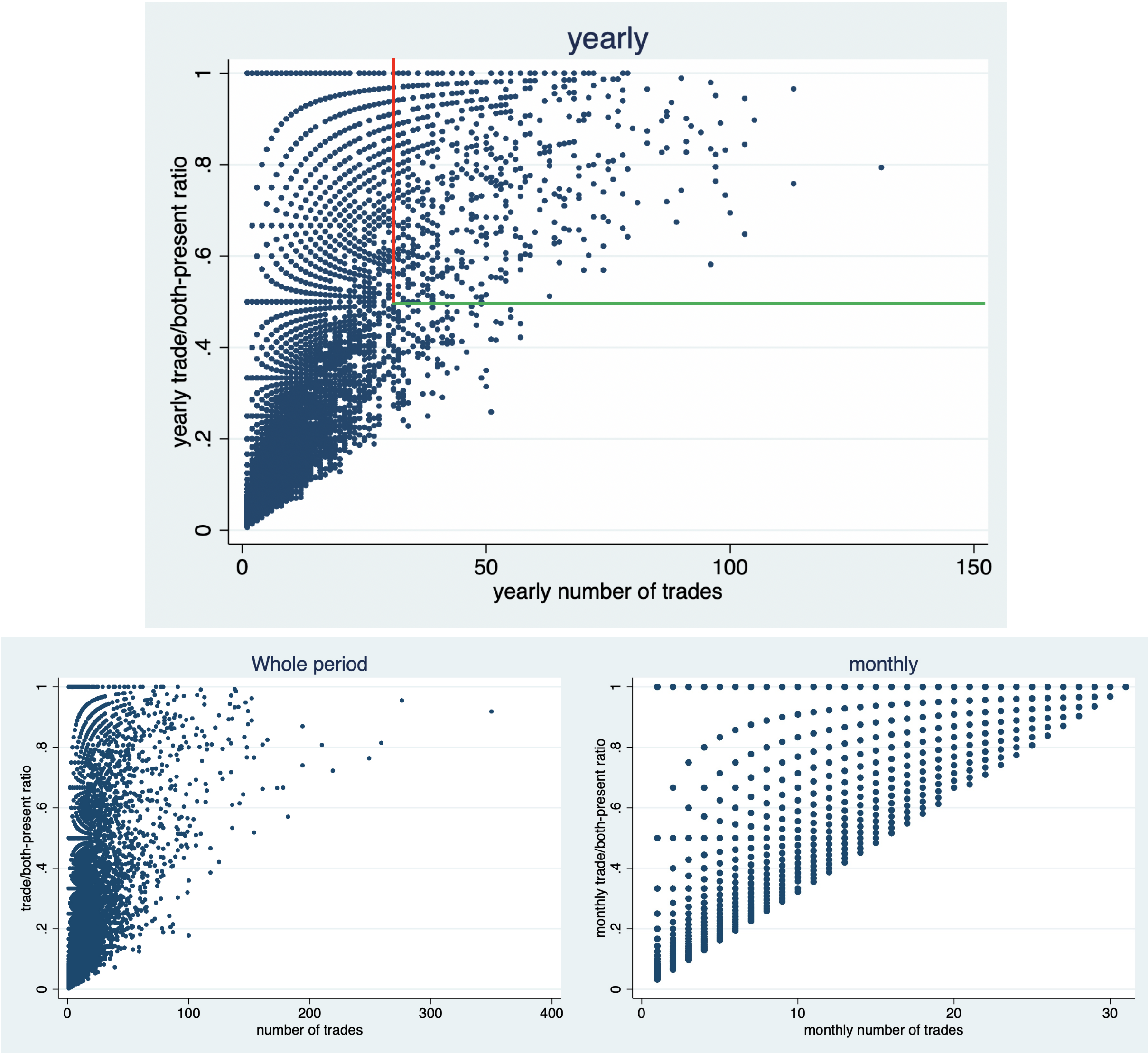

Figure 7: tp ratio versus number of days the buyer and seller trade

Table 3: Summary statistics: relationships (cauliflower)

Variable	Obs.	Mean	Standard Dev.	Min.	Max
Panel A: Relationship characteristics					
Avg. number of trades per year	557	48	16	30	131
Avg. trading Volume per year (kg)	557	52,848	38,092	7,582	254,052
Avg. number of days both are present per year	557	63	22	31	165
Avg. yearly tp ratio	557	0.77	0.14	0.51	1
Avg. number of trades per month	557	12	4	5	27
Length (in days)	557	228	209	33	1199
Frequency (avg. time-gap between two subsequent transactions)	557	4	3	1	14
Panel B: Number of relationships per buyer and seller					
Number of relationships per buyer	362	1.54	0.89	1	5
Number of relationships per seller	63	8.84	8.06	1	35

4 Conceptual Framework

Relational contracts differ from a formal, written contract in the sense that the promises exchanged cannot be verified and enforced by a third party. The contracting parties rely solely upon the future rewards or punishments to sustain their relationships. Thus, repeat trading is necessary, as inter-temporal incentives are the only tool to discipline short-term opportunism. I set up a simple framework in which relationships are supported by relational contracts. The parsimonious framework dispenses with unnecessary details but captures the key aspects of the relationship between a buyer and a seller in this market.

4.1 Conceptual foundation

A buyer (she) and a seller (he) potentially interact an indefinite number of periods, $t = 0, 1, ...$, and share a common discount factor $\delta < 1$. A relational contract negotiated in period t is given by $C_t = \{q_t, p_t\}$. Figure 11 shows the timeline of the game.

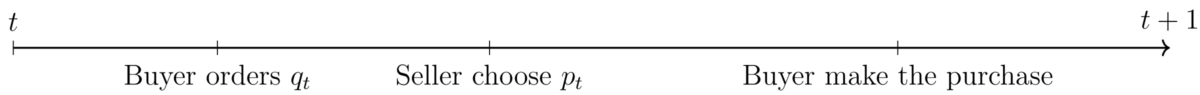

Figure 8: Timeline of the game

Denote with U_t and V_t the net present value of the payoffs from the relationship at time t for the buyer and the seller respectively. The value of a RC in this setting lies in the assuredness of selling or buying opportunities in future periods. The expected surplus from a relationship is $S_t^R = U_t + V_t - U_t^0 - V_t^0$.

For a RC to be self-enforcing, the long-term benefit must outweigh the gain from one-time deviation. The self-enforcement constraint (Levin, 2003; also known as the "incentive compatibility constraint" in Baker, Gibbons or Murphy (2002) and "dynamic enforcement constraint" in Board (2011)) for the buyer to abide by the relational agreement is:

$$\frac{\delta}{1-\delta}(U_t - U_t^0) \geq \pi_t^B(p_t, F(p)_t, c_B) \tag{1}$$

where U_t^0 is the value of the buyer's outside option at time t. π_t^B denotes one-time gain from defaulting on the contract. It is essentially the difference between p_t and the lowest price offer the buyer could potentially get, $\underline{p}_t$, taking into account the buyer's search cost: $\pi_t^B = \pi_t^B((p_t - \underline{p}_t) * q_t | c_B)$. Thus, it is related to p_t, the price distribution in the market $F(p)_t$, as well as the buyer's search cost c_B. Essentially, $F(p)_t$ is determined by the relative supply and demand conditions at the market. The self-enforcing constraint captures the idea that the buyer will not shirk on her promised loyalty providing the future relationship-specific gain is higher than the one-time gain from defection.

The seller's self-enforcement constraint is:

$$\frac{\delta}{1-\delta}(V_t - V_t^0) \geq \pi_t^S(p_t, F(p)_t) \tag{2}$$

The seller chooses p_t to maximize his profit subject to (1) and (2). $\pi_t^S = (\overline{p}_t - p_t) * q_t$, where $\overline{p}_t$ is the highest price the seller could potentially sell q_t at (to another buyer), and is thus related to the relative supply and demand conditions at the market.[3]
The left hand sides of (1) and (2) reflect the value of the relationship, while the right hand side is determined by both the seller's price quote p_t and the market condition at t. I distill three testable hypotheses from the extant literature that are derived mainly from these constraints.

4.2 Testable hypotheses

Hypothesis I. **An existing relationship significantly affects transaction prices**.

This hypothesis follows naturally from RC theory and empirical findings in various markets. If a relationship is feasible then there exists an invariant RC which is optimal and gives any division of the total surplus available (Board, 2011). While "idiosyncratic transactions" feature the maximum level of profit maximization in a single-shot game, "relational transactions" do not, as buyers and sellers endogenize the future benefit of the relationship. Thus, everything else equal, price of a relational transaction can be different from that of a idiosyncratic one.

[3] It also depends on how many buyers visit the seller, which is affected by how many buyers are present, how many relational buyers he has, etc. Yet this is hard to define or predict.

Di Maggio et al. (2017) find evidence in the OTC corporate bond market that bilateral inter-dealer relations lower markups significantly. Gallegati et al (2011) show that buyers who have a relational seller obtain systematically lower prices in the Ancona wholesale fish market. Kirman and Vriend (2001) also find that sellers offer higher utility to loyal buyers in the Marseille wholesale fish market. In my context, based on Hypothesis I, I should be able to detect significant price difference between relational and idiosyncratic transactions.

Hypothesis II. **Traders behave strategically under exogenous shocks to maintain their relationships**.

The incentive compatibility constraint reveals the mechanism through which exogenous shocks erode the parties' ability to sustain a relationship. There is a direct temptation mechanism operating through the RHS of the constraints. An exogenous shock generates variation in the seller's or the buyer's temptation to default. For example, when supply drops unexpectedly, driving price up, the benefit of one-time deviation increases for the buyer as the relative cost of search decreases. This tightens constraint (1) and forces the seller to lower his price quote if he wants the buyer to stay. In other words, to maintain a relationship, trading parties may be willing to incur a short-term loss in exchange for a future benefit (Beckmann and Boger, 2004).

If the constraints are binding, a small unanticipated shock should lead to breakups of relationships (Macchiavello and Morjaria, 2015). If not, the shock has to be large enough to trigger a deviation. Di Maggio et al.(2017) show that dealers exploit the benefit of trading relationships more forcefully in times of market turmoil: they demand higher spreads during periods of high uncertainty. In my setting, traders might also benefit from the trading partners that are dependent on them under exogenous shocks. Given that a relationship survived under an exogenous shock, the transaction price p_t reflects a strategic response of the trading parties to the slack of the self-enforcement constraint. By defining large supply swings that are not predictable by seasonality, I would be able to see if the price response to supply shock is different between relational transactions and idiosyncratic transactions.

Hypothesis III. **The value of a relationship changes as it ages, and depends on**

its intensity.

The slackness in the self-enforcement constraints is largely determined by S_t, the relationship-specific surplus that the parties can earn from continuing the relationship (Micheler and Wu, 2019). The higher S_t is, the more relaxed these constraints become. As a result, the way a relationship affects transaction prices might change as it evolves. The effect should also be heterogeneous across buyer-seller pairs that have different trading intensity.

Macchiavello and Morjaria (2015) show that the value of a relationship increases with the relationship's age. Longer relationships can relax the self-enforcement constraints through learning about the seller's reliability. Antras and Foley (2015) find that in the early stages of a relationship, the temptation for the customer to default is high. As the relationship ages, the continuation value of the contract is greater than the one-time gain from default. As a result, the longer the relationship, the more flexible the financing terms. Di Maggio et al. (2017) measure the intensity of a trading relationship using the fraction of previous sales and purchases between the two in each party's trade profile. They find that profit margins are lower in transactions between parties having a stronger tie. Heise (2019) proves that relationship will accumulate capital (e.g., trust) over time and the increase in such capital is substantial when the trading parties experience exogenous shocks. Relationships that have received relatively strong idiosyncratic shocks and do not breakdown have increased their capital sufficiently. These relationships therefore have relatively low transaction costs, and a greater capacity to buffer risk.

The next section tests these predictions and finds support for all of them in the data.

5 Empirical Analysis

5.1 Baseline econometric model

The baseline regression estimates the impact of various factors on the price of a single transaction.

$$
\begin{aligned}
P_{i,j,t} = {} & \omega_1 \textbf{ transaction volume}_{i,j,t} + \omega_2 \textbf{ share in } \boldsymbol{i}\textbf{'s sales}_{i,t} \\
& + \omega_3 \textbf{ share in } \boldsymbol{j}\textbf{'s purchase}_{j,t} + \omega_4 \textbf{ late}_{i,j,t} + \\
& + \gamma_1 \textbf{ yesterday's avg. price}_t + \gamma_2 \textbf{ market total trading volume}_t \\
& + \gamma_3 \textbf{ positive supply shock} + \gamma_4 \textbf{ negative supply shock} \\
& + \gamma_5 \textbf{ number of buyers low} + \gamma_6 \textbf{ number of sellers low} + \gamma_7 \textbf{ buyer-seller ratio} \\
& + \sum \mu_h M_h + \sum \tau_l Y_l + \theta_i + \epsilon_{i,j,t}
\end{aligned} \tag{3}
$$

where $P_{i,j,t}$ is the transaction price between seller i and buyer j on day t. The explanatory variables include transaction specifics : volume, share of this transaction in seller i's total sales on day t, share of this transaction in buyer j's total purchase on day t, whether this transaction happened in late hours; and variables capturing market condition at t: total trading volume, yesterday's average price at the market, whether the number of sellers or buyer is low at time t and the ratio of number of buyers to the number of sellers at time t.[4] Introducing transaction volume to the RHS exposes the model to the problem of endogeneity – volume can be endogenous to price. Yet as mentioned in section 3, buyers in this market often specify their volume ex ante without knowing the price. This reduces the potential endogeneity to a large extent.

To capture dramatic changes in supply, I break a year into two-week-long periods and compute the mean daily sales.[5] I then define days when supply is one standard deviation below the mean as a day with low supply (negative supply shock), and one standard deviation above the mean as a day with high supply (positive supply shock). Month (M_h),

[4] Preliminary examination shows that there is not a systematic declining pattern of prices over the course of a day, but on some days prices drop in late hours. So a dummy variable "late" is introduced to indicate that the transaction took place after 11:00 am. Currently, I define days when the number of sellers is less than 10 as days the number of sellers is low. The number of buyers is low if it is less than 50. In the future I will use the daily seller/buyer HHI to set the cutoff instead.

[5] Fixed, not on a rolling basis.

year (Y_l) and seller (θ_i) fixed effects are also included. Quality difference, if any, can be controlled for using seller fixed effects.

5.2 Testing hypotheses

Hypothesis I. An existing bilateral relationship significantly affects transaction the price.

I test this hypothesis by introducing a dummy variable "**relationship**" to the baseline regression. The dummy variable "**relationship**" equals one if the transaction is characterized as "relational", i.e., the buyer and the seller are bound by a RC when this transaction happens.

$$\begin{aligned} \mathbf{P}_{i,j,t} &= \alpha_1 \, \mathbf{relationship}_{i,j,t} + \Omega \mathbf{Z}_{i,j,t} + \Gamma \mathbf{X}_t \\ &+ \sum \mu_h M_h + \sum \tau_l Y_l + \theta_i + \epsilon_{i,j,t} \end{aligned} \tag{4}$$

The vector $\mathbf{Z}_{i,j,t}$ includes controls specific to the particular transaction, and vector $\mathbf{X}_t$ include controls regarding market conditions on day t, the same as in model (3).

One novel feature of the data is that it allows me to compare "relational transactions" a single seller made to the "idiosyncratic transactions" he made on the same day, while in most existing RC studies these two exchange forms do not co-exist. Price differences between relational and idiosyncratic transactions can be explained as the seller/buyer's strategic response to satisfy the incentive compatibility constraint.

Although the division of the relationship-specific surplus must be that the IC constraints are satisfied, we have no prior judgement of the sign of the coefficient of "**relationship**". If the coefficient is negative, it suggests that buyers benefit from repeated transactions in general; if it is positive, it suggests that sellers capture a larger share of the surplus.

Hypothesis II. Traders behave strategically under exogenous shocks to maintain their relationships.

The test relies on exogenous variation in the buyer/seller's temptation to default. To test this hypothesis, I investigate the effect of relational contracts on transaction prices in days when there is a supply shock. Interaction terms of the relationship dummy and supply shock (positive and negative) dummies are introduced in specification (5). If traders exploit the benefit of trading relationships in times of unexpected supply changes, the coefficient of the interaction terms shall be significant.

$$\begin{aligned}\mathbf{P}_{i,j,t} = \alpha_1 \,\mathbf{relationship}_{i,j,t} + \alpha_2 \,\mathbf{relationship}_{i,j,t} \times \mathbf{positive\ supply\ shock}_t \\ + \alpha_3 \,\mathbf{relationship}_{i,j,t} \times \mathbf{negative\ supply\ shock}_t + \Omega \mathbf{Z}_{i,j,t} + \Gamma \mathbf{X}_t \\ + \sum \mu_h M_h + \sum \tau_l Y_l + \theta_i + \epsilon_{i,j,t}\end{aligned} \tag{5}$$

Table 4: Test Results of Hypothesis I & II

	(1) Price	(2) Price	(3) Price
Relationship	0.178***	0.174***	0.173***
	(0.045)	(0.021)	(0.023)
Relationship × Positive shock			0.079***
			(0.021)
Positive supply shock	−0.131***	−0.113***	−0.125***
	(0.034)	(0.029)	(0.031)
Relationship × Negative shock			−0.071**
			(0.043)
Negative supply shock	0.057	0.100**	0.113***
	(0.052)	(0.040)	(0.043)
Seller fixed effect		Y	Y
R^2	0.581	0.572	0.573

Robust standard errors clustered at the seller level. Significance levels: *** = 1%, ** = 5%, * = 10%. Number of observations = 111,535.

Column (1) and (2) in Table 4 report the coefficient estimates relating transaction price to the transaction type – relational or idiosyncratic. Column (1) does not include seller fixed effect. Column (3) adds the interaction terms. The coefficients of "**relationship**" are positive and significant across all specifications. On most trading days the average price of cauliflower falls between ¥2 -¥4. Thus, there is on average a price premium of 4% to 8% associated with relational transactions. The coefficient of "**negative supply shock**" (a significant decrease in supply) is positive, while the coefficient of "**relationship × negative shock**" is negative, indicating that sellers give lower prices to their relational buyers than idiosyncratic buyers while prices increase in general when there is a negative supply shock. In other words, sellers give discount to buyers who are most dependent on them to prevent them from deviating. For a positive shock (an unexpected increase in supply), the coefficient of "**positive shock**" alone is negative, while that for "**relationship × positive shock**" is positive. When price decreases as supply becomes unusually abundant, relational buyers are willing to pay a higher price. In essence, this means relationships become more valuable in turbulent times and trading parties mutually insure each other.

Hypothesis III. The value of a relationship changes as it ages, and depends on its intensity.

I now turn to a more in-depth analysis of the role of prior interactions in determining the value of a relationship. I explore the impact of relationship age and strength on transaction prices. Formally, I estimate model (6) using the sub-sample containing relational transactions only.

$$\begin{aligned}
\mathbf{ln(P)}_{i,j,t} = {} & \beta_1 \ \mathbf{fraction\ selling\ to\ counterpart}_{i,j,t} \\
& + \beta_2 \ \mathbf{fraction\ buying\ from\ counterpart}_{i,j,t} \\
& + + \beta_3 \ \mathbf{ln(cumulative\ number\ of\ trades)}_{i,j,t} \\
& + \beta_4 \ \mathbf{ln(number\ of\ positive\ shocks\ gone\ through)}_{i,j,t} \\
& + \beta_5 \ \mathbf{ln(number\ of\ negative\ shocks\ gone\ through)}_{i,j,t} \\
& + \theta_1 \ \mathbf{ln(age)}_{i,j,t} + \Omega \mathbf{Z}_{i,j,t} + \Gamma \mathbf{X}_t + \sum \mu_h M_h + \sum \tau_l Y_l + \theta_i + \lambda_j + \eta_{i,j} + \epsilon_{i,j,t}
\end{aligned} \tag{6}$$

The first five independent variables are used as proxy of the relative intensity of a relationship at t. I compute the fraction of sales seller i had with buyer j in a given month, normalized by the i's total sales. "**Fraction selling to counterpart**" is the average of this fraction in the previous three months. "**Fraction buying from counterpart**" is calculated in a similar fashion. "**Cumulative number of trades**" sums all transactions made between the buyer-seller pair since their first trade. The last two variables that measure relationship intensity are the **number of positive/negative shocks** the trading parties have experienced up to this point. The **age** of a relationship is defined as the number of days since their first trade. As the explanatory variables take a wide range of value, I transform all continuous variables into their logarithm forms to reduce the instability of the model.

Table 5: Test Results of Hypothesis III

	(1) Price (ln)	(2) Price (ln)	(3) Price (ln)
Age (ln)	−0.002*	−0.013*	−0.006
	(0.010)	(0.008)	(0.010)
Relationship strength			
Fraction selling to counterparty ([0,1])	−0.258***	−0.085***	−0.024*
	(0.103)	(0.126)	(0.157)
Fraction buying from counterparty ([0,1])	0.015*	0.004	0.039**
	(0.023)	(0.019)	(0.019)
Number of positive shocks (ln)	0.017	0.014	0.018**
	(0.008)	(0.009)	(0.009)
Number of negative shocks (ln)	0.020**	0.026***	0.027*
	(0.009)	(0.008)	(0.015)
Cum. number of trades (ln)	−0.035***	−0.031**	−0.059**
	(0.013)	(0.015)	(0.024)
Fixed effects	Pair-wise	Buyer	Seller
R^2	0.817	0.816	0.808

Robust standard errors clustered at (1)-(3): pair level, (4): buyer level and (5): seller level .
Significance levels: *** = 1%, ** = 5%, * = 10%. Number of observations = 13,876.

Table 5 reports the estimation results. Column (1)-(3) includes pairwise fixed effects, $\epsilon_{i,j,t}$, column (4) includes buyer fixed effects, λ_j and column (5) includes seller fixed effects. Buyer fixed effect allow comparison across a buyer's relationships, while seller fixed effect allow comparison across a seller's relationships. However, as the four-year data does not necessarily contain the whole period of a relationship since its establishment, the measures of age and intensity can be inaccurate. Controlling pairwise fixed effects could mitigate this caveat.

On average, a higher fraction of past sales from the seller to the buyer leads to a lower price. On the other hand, a higher fraction of purchases by the buyer from the seller, predicts a higher price. When the number of transactions increases, the model predicts an increase in price, although the effect is not economically significant. The effect of exogenous shocks gone through is not significant in general. When relationship intensity is controlled for, age has a negative impact on price, while its impact alone is positive. When buyer or seller fixed effects are included, most of the coefficient estimates have the same signs.

6 Concluding remarks

The regression models fit the data well. Nearly all of the coefficients have the anticipated signs, most are significant at conventional levels, and the overall explanatory power of the models, as measured by adjusted R^2, is satisfactory.

The results of the three tests confirm the importance of trading relationships in the formation of transaction prices. Relational buyers in general are paying a price premium. The surplus generated by the RC is allocated more to the seller. The reason could be that the buyer is getting reduced price risk, and greater assuredness of supply. This finding goes against the traditional wisdom that repeated trading reduces price for a buyer.

In addition, relationships become more important under exogenous shocks. Both the seller and the buyer benefit from their relationships when supply makes large swings. Sellers are willing to charge lower prices when price increases market-wide, while buyers are willing to pay more when price decreases market-wide. In other words, price reduction is less in relational transactions when supply becomes unexpectedly abundant, and price increase is less when supply drops dramatically. Traders absorb part of the price risk for their contractual partner and the relationship functions as a mutual insurance in protecting each other. This can be a strategy to maintain the relationship.

Lastly, the price effect of a relationship changes as it evolves. Similar to Macchiavello and Morjaria (2015), Di Maggio et al.(2017) and other studies discussed earlier, this study affirms the discovery that the importance of existing relations is time-varying. Relationship intensity also proves essential in explaining the price differences. Traders are willing to share surplus with the trading partners that they are mostly dependent upon.

To sum, relationship-based strategic pricing explains, to a significant extent, the observed price dispersion in this market. Trading relationships prove to be important in determining transaction prices. To further explain the price dispersion, however, the influence of the ways agents interact, not only through bilateral relationships but a network of connections, should be taken into consideration. Examples in the literature include Vignes and Etienne (2011), who consider the fish market as a seller-seller network and link price dispersion to the role of sellers' position in the network; and Hendershott et al. (2019), who investigate how network of relationships shape the trading behavior in the OTC corporate bond market. The latter find that traders build networks that they search randomly within and prices depend on network size. Future studies should consider networks between sellers and buyers as well as those among buyers and among sellers, and use them to further explore pricing dynamics in the market.

7 References

Abreu, D. (1988). On the theory of infinitely repeated games with discounting. Econometrica, 383-396.

Antras, P., & Foley, C. F. (2015). Poultry in motion: a study of international trade finance practices. Journal of Political Economy, 123(4), 853-901.

Baker, G., Gibbons, R., & Murphy, K. J. (1994). Subjective performance measures in optimal incentive contracts. The Quarterly Journal of Economics, 109(4), 1125-1156.

Baker, G., Gibbons, R., & Murphy, K. J. (2002). Relational Contracts and the Theory of the Firm. The Quarterly Journal of Economics, 117(1), 39-84.

Beckmann, V., & Boger, S. (2004). Courts and contract enforcement in transition agriculture: theory and evidence from Poland. Agricultural Economics, 31(2-3), 251-263.

Board, S. (2011). Relational contracts and the value of loyalty. American Economic Review, 101(7), 3349-67.

Crespi, J. M., & Sexton, R. J. (2004). Bidding for cattle in the Texas Panhandle. American Journal of Agricultural Economics, 86(3), 660-674.

Di Maggio, M., Kermani, A., & Song, Z. (2017). The value of trading relations in turbulent times. Journal of Financial Economics, 124(2), 266-284.

Gallegati, M., Giulioni, G., Kirman, A., & Palestrini, A. (2011). What's that got to do with the price of fish? Buyers behavior on the Ancona fish market. Journal of Economic Behavior & Organization, 80(1), 20-33.

Graddy, K., & Hall, G. (2011). A dynamic model of price discrimination and inventory management at the Fulton Fish Market. Journal of Economic Behavior & Organization, 80(1), 6-19.

Halac, M. (2012). Relational contracts and the value of relationships. American Economic Review, 102(2), 750-79.

Heise, S. (2019). Firm-to-firm relationships and the pass-through of shocks: Theory and evidence. FRB of New York Staff Report, (896).

Hendershott, T., Li, D., Livdan, D., & Schürhoff, N. (2019). Relationship trading in OTC markets. Journal of Finance, in press.

Levin, J. (2003). Relational incentive contracts. American Economic Review, 93(3), 835-857.

Klein, B., & Leffler, K. B. (1981). The role of market forces in assuring contractual performance. Journal of political Economy, 89(4), 615-641.

Kirman, A. P., & Vriend, N. J. (2001). Evolving market structure: An ACE model of price dispersion and loyalty. Journal of Economic Dynamics and Control, 25(3-4), 459-502.

Kranton, R. E. (1996). The formation of cooperative relationships. The Journal of Law, Economics, and Organization, 12(1), 214-233.

Macchiavello, R., & Miquel-Florensa, P. (2018). Vertical integration and inter-firm relationships: Evidence from the Costa Rica coffee chain. Working Paper, London School of Economics.

Macchiavello, R., & Morjaria, A. (2015). The value of relationships: evidence from a supply shock to Kenyan rose exports. American Economic Review, 105(9), 2911-45.

Macchiavello, R., & Morjaria, A. (2019). Competition and relational contracts in the Rwanda coffee chain. Working Paper, Northwestern University.

MacLeod, W. B., & Malcomson, J. M. (1989). Implicit contracts, incentive compatibility, and involuntary unemployment. Econometrica: Journal of the Econometric Society, 447-480.

Michelson, H., Reardon, T., & Perez, F. (2012). Small farmers and big retail: trade-offs of supplying supermarkets in Nicaragua. World Development, 40(2), 342-354.

Michler, J. D., & Wu, S. Y. (2019) Relational Contracts in Agriculture: Theory and Evidence. Working Paper, Purdue University.

Rao, E. J., Brümmer, B., & Qaim, M. (2012). Farmer participation in supermarket channels, production technology, and efficiency: the case of vegetables in Kenya. American Journal of Agricultural Economics, 94(4), 891-912.

Sapio, S., Kirman, A., & Dosi, G. (2011). The emergence and impact of market institutions: The wolesale market for fish and other perishable commodities (No. 2011/14). LEM Working Paper Series.

Telser, L. (1980). A theory of self-enforcing agreements. Journal of Business, 53:27–44.

Vignes, A., & Etienne, J. M. (2011). Price formation on the Marseille fish market: evidence from a network analysis. Journal of Economic Behavior Organization, 80(1), 50-67.

Weisbuch, G., Kirman, A., & Herreiner, D. (2000). Market organisation and trading relationships. The Economic Journal, 110(463), 411-436.