Relational Adaptation in Spot Trading *

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We study adaptation via relational contracting alongside active spot trading. Employing unique and rich transaction data from a large wholesale vegetable market, we show that (i) facing stochastic supply and competition, buyers pay a price premium to relational sellers in exchange for relational contracts (RCs) that provide supply assurance; (ii) RCs are more likely to be formed in the presence of more competing buyers given the number of sellers and aggregate supply; and (iii) relational traders adjust contractual terms after the realization of supply shocks, contributing novel empirical evidence on relational adaptation by non-integrated traders.

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I. Introduction

Increasing disruptions in the supply chains, due to weather shocks, epidemics, and geopolitical conflicts among other local and global shocks (Grossman, Helpman and Lhuillier, 2023), highlight the ever-changing environment in which economic agents trade. To economic agents, individuals or firms, adapting to the changing environment has been considered central to their survival and prosperity (Williamson, 2005).

Economic relationships between agents help adaptation. Specifically, a relational contract (RC), self-enforcing agreements governed by the mutual future value of continuing the relationship, allows non-integrated (Klein and Murphy, 1997) or integrated agents (Williamson, 1975) to adapt to changed circumstances *ex post* based on unique knowledge: outcomes that are observed only by the trading agents, not a third party, and/or impossible to specify *ex ante* (Baker, Gibbons and Murphy, 2002). Adaptation via forming RCs, or relational adaptation, helps maximize the joint expected payoffs of agents (Baker, Gibbons and Murphy, 2011).[1]

Despite rich theoretical insights on relational adaptation, empirical investigation is limited. Empirical work on relational contracting in various contexts estimates the value of relationships (McMillan and Woodruff, 1999), price and markup effects of relationships (Cajal-Grossi, Macchiavello and Noguera, 2023), examines strategic defaults on relationships (Blouin and Macchiavello, 2019), and more.[2] There is, however, little empirical evidence on adaptation to shocks *ex post* via RCs; little empirical evidence shows that actions of relational traders are strategically adjusted based on the state of the world (Baker, Gibbons and Murphy, 2011).

We provide novel evidence of relational adaptation amidst active spot trading. Our transaction-level data come from a well-functioning agricultural wholesale market where many buyers and sellers trade a homogeneous commodity from day to day. In this highly competitive market, we document a large number of repeatedly trading pairs. We show theoretically and empirically that 1) buyers may form RCs with sellers, paying a price premium to obtain supply assurance against frequent demand and supply fluctuations in the marketplace; 2) the buyer's incentive to form an RC is stronger, when the number of buyers is larger given the aggregate supply; and 3) relational traders adapt to market-level supply swings *ex post* by strategically adjusting the terms of their RC to sustain the relationship for higher joint payoffs in expectation.

[1]More precisely, relational adaptation helps maximize payoffs only if the agents choose the appropriate governance form. Governance forms refer to spot (i.e., non-integration) and within-firm (i.e., vertical integration) trading in the literature of adaptation (Gibbons, 2005). In the empirical literature on relational contracting, in contrast, RC itself is considered a governance form (Macchiavello, 2022). While we refer to both strands of literature, whether defining RC as a governance form does not significantly affect our analysis.

[2]Macchiavello and Morjaria (2022) provides a recent literature survey of empirical studies on relational contracting.

Our analysis begins by scrutinizing the marketplace in Section II. With a total yearly volume traded exceeding 3.0 million metric tons, the wholesale market is among the largest wholesale produce markets in Asia. It shares several key features with agricultural wholesale markets in low- and middle-income countries (LMICs) — a large number of sellers and buyers, on-site negotiation for price and quantity by transaction, and highly homogeneous products. Demand and supply fluctuate from day to day due to weather shocks, entry and exit of traders, and other exogenous factors. All transactions are completed on-site, eliminating delivery or payment risks. Neither trader needs to invest in any specific asset for transactions, either, rendering concerns on property rights irrelevant.

Transaction information, including trader identifier, price, and quantity traded, is recorded in a digital system when the traders weigh products on the market scale and pay cash via the market cashier. The administrative, transaction-trader-time-specific dataset has three key advantages. First, it provides a complete history of transactions for each pair of traders, allowing us to observe if and when repeated trade occurs and to what extent. Prior empirical studies on RCs mostly rely on established relationships (Macchiavello and Morjaria, 2015; Ghani and Reed, 2022). Second, the dataset covers a much larger number of traders and much higher-frequency transactions than data used in most previous research like Antras and Foley (2015) and Blouin and Macchiavello (2019). Third, our data are largely exempt from measurement errors because traders lack the incentive and ability to misreport prices or volumes in the digital system as explained in Section II.B. In contrast, data obtained from field surveys and firm or industry reports likely suffer from nontrivial measurement errors due to, for instance, inaccuracies or bias in recall information (Beegle, Carletto and Himelein, 2012).

We employ data spanning a four-year period from 2016 to 2019, focusing on transactions of Chinese cabbage, the most traded commodity by volume in this wholesale market and in China. Three stylized facts stand out. First, prices are significantly dispersed within a single day and even for a given seller on the day. The within-seller-day price dispersion remains, controlling for 1) the volume of the transaction (e.g., 1200 kilograms) and 2) the timing of the transaction (e.g., 9:08 a.m.). Second, repeated trade, a buyer and a seller transact with each other for a significant number of times, is pervasive. Third, by exploiting the repeated transactions, we find that the volume purchased by a buyer who conducts repeated trade tends to be more stable and such a buyer is less likely to be rationed under his/her desired amount, especially under negative market-level supply shocks.

The stylized facts motivate a conceptual framework built in Section III that characterizes the dynamic incentive compatibility constraints for buyers and sellers who potentially form RCs via repeated transactions. We show that an RC effectively provides informal supply insurance to buyers who pay sellers a price premium in exchange for the assurance of supply. The incentive for RCs is stronger, when the risk of being rationed rises for a buyer. Given the number of active sellers and the aggregate supply, a larger number of active buyers, in particular, increases the value of relational contracting. The model suggests, further, that relational traders need to adjust contractual terms, after aggregate supply shocks are realized, to sustain the relationship for higher joint expected payoffs. Specifically, when the aggregate supply falls (rises), the RC premium rises (falls) to maintain the dynamic incentive compatibility constraints, which is realized by partial pass-through from spot to relational prices.

Section IV tests and provides supporting evidence for the hypotheses of the model. In the baseline test, we find that prices charged by sellers are on average 2–4% higher for RC buyers than for spot buyers, controlling for seller-day fixed effects, buyer characteristics (e.g., buyer's average volume purchased), and transaction characteristics (e.g., size and time of the transaction). This magnitude is economically significant given the narrow profit margin of vegetable wholesaling. Evidence confirms that RCs are more likely to be formed, when there are more buyers given the aggregate supply and the number of sellers. By examining newly formed relationships, we further show that buyers experience significantly more frequent negative supply shocks, which indicate higher risks of being rationed, a short window before they start forming RCs than in other periods. When the aggregate supply drops (rises) significantly relative to the rolling average, the RC premium decreases (increases) as the model suggests. Our baseline results are robust to alternative definitions of an RC, supply shocks, and sub-samples.

Section V first presents a few key extensions to the conceptual model. We discuss and dismiss several alternative explanations for repeated trade, price dispersion, and relationship formation. For instance, while search and price discrimination could result in price dispersion for a homogeneous product, they do not align with the price premium we identify for relational buyers. We also find that relational buyers trade in a relatively narrow window of time compared with spot buyers, suggesting that the desire for flexible trading time is unlikely the key incentive for building relationships. We hence argue that, though supply assurance may not be the only incentive for building relationships, it is an empirically plausible mechanism that is consistent with key data patterns we document. We then examine the drivers of strategic defaults and RC termination, finding patterns that echo insights from the previous sections.

Our findings stand out from the existing literature in three ways. First, empirical investigations into relational contracts are mostly based on institutionally weak settings where spot and firm transactions are inherently inefficient due to problems such as asymmetric information (Levin, 2003), high risks of delivery failure (Macchiavello and Morjaria, 2015), weak contract enforcement (Brugues, 2023), or missing credit provision (Antras and Foley, 2015). RCs play a critical role in overcoming market frictions and disciplining opportunistic behavior of traders in such contexts. The spot trading environment we observe, in contrast, has homogeneous products, and all transactions involve immediate cash transfers and delivery of products. This renders common transaction frictions irrelevant; the rationale for relational contracting alongside well-functioning spot trading must lie beyond these considerations. We argue that the risk of being rationed gives the buyer the incentive to form an economic relationship as an informal supply insurance, echoing Cajal-Grossi, Macchiavello and Noguera (2023).[3]

Second, we are one of the first to empirically test the determinants of incentives for building relationships. In our context, trading relationships evolve out of active spot trading. Traders start with the default choice of engaging in spot trading and may establish relationships anticipating frequent shocks. We show that the incentive to form RCs strengthens, when more buyers compete for the given aggregate supply. The dynamic process of forming RCs confirms that market conditions before RCs are formed imply a lower residual supply for buyers. In most prior studies, RCs are already established and taken for granted. Studies showing the RCs may break under certain shocks help infer determinants of RC incentives (Macchiavello and Morjaria, 2021). They, however, do not observe the dynamics in forming or terminating relationships as we do.

Third and foremost, we empirically examine relational adaptation to frequently changing market conditions between non-integrated agents. Relational traders strategically adjust contractual terms after the realization of shocks. The ability to adapt post shocks is a unique advantage of RCs over pure spot trading (Baker, Gibbons and Murphy, 2011). Ghani and Reed (2022) examine changes in RC terms following a structural transformation of Sierra Leone's ice industry, which involves a one-shot adaptation. We show, instead, that relational traders constantly adapt to shocks by adjusting RC terms without altering the RC's primary value as quantity insurance. Gil, Kim and Zanarone (2022) document that major U.S. airline carriers restructure RCs with regional partners following the 2008 Financial Crisis. Again, the terms of RCs were permanently changed after one drastic shock in their context. Non-integrated relational traders we study, in contrast, face relatively small, transitory, frequent, and idiosyncratic shocks and make temporary adjustments to RC terms to achieve strategic adaptation.

II. Background, Data, and Stylized Facts

Wholesale markets offer the dominant channel through which agricultural products are marketed from farm gate to catering and retail in LMICs. In China, more than 70% of fresh produce was traded via wholesale markets before being transported downstream to domestic and foreign consumers as of 2019. This section introduces the Chinese wholesale market of interest, the transaction data employed for our analysis, and three key facts revealed by the data.

[3]Focusing on a wholesale fresh fish market, Weisbuch, Kirman and Herreiner (2000) find that the value of repeated trade for buyers is to avoid the risk of not being served. Their study, however, is not built upon the theory of economic relationships and hence provides no discussion on relational adaptation.

A. The Marketplace

The wholesale market of interest is located in northern China. Every year, 3-4 million metric tons of vegetables are traded in the marketplace, amounting to annual sales of 7-10 billion RMB (1-1.5 billion USD). As one of the largest wholesale fresh vegetable markets in China and Asia, this is a so-called *primary* wholesale market that connects directly to the farm gate. For supply chains that are long and consist of multiple stages, *secondary* wholesale markets procure from an upstream, often larger-scale wholesale market.

More than 300 fresh vegetables are traded on the market (e.g., broccoli, cabbage, celery, and tomatoes) over a year and then shipped to more than 200 cities all over China as well as overseas. Fresh vegetable products receive minimal packaging and processing, having limited quality differentiation. The market opens daily from early morning (4-5 a.m.) to late afternoon (5-6 p.m.). Due to the limited storage capacity provided by the market, products brought by sellers are typically sold out within a day. For many vegetables, markets often clear before noon on the day they are marketed.

Each day, a large number of buyers (she) and sellers (he) come to trade face-to-face. No price is posted. Sellers display their products in the open air, and buyers can freely walk around to check products and talk with sellers (see Figure A1 for market scenes), negotiating price and quantity of a potential transaction. For most vegetables, there are more buyers than sellers on the market. Most traders are professional vegetable traders and have been in the business for years.

About 80% of the sellers collect vegetables directly from smallholder producers, while other sellers purchase from larger-scale farms and/or farm cooperatives located in various production regions (Song, 2023). Within each production season, many sellers specialize in selling one vegetable. Sellers use open-air trailer trucks or cold storage trucks to carry the products. Each seller comes to the market with a pre-committed supply on a day (e.g., two truckloads of Chinese cabbage) that cannot be altered within the day. Due to high transport costs, sellers typically fill up each truck they bring to the market.[4]

Buyers are small-to-medium-scaled and can be classified into three types: 1) wholesalers who sell products procured from this primary market to buyers on a secondary wholesale market, 2) agents who procure on behalf of retail stores, and 3) those procuring for restaurants or canteens. Each buyer has an optimal amount to purchase that is determined by downstream obligations and market conditions. There are capacity constraints on the buyer side, too, because each buyer can at most fill up her truck(s) on a given day.

Like many wholesale markets in LMICs, prices are not posted and are negotiated transaction by transaction. Once a seller and a buyer settle a deal, the buyer pays in cash and loads the products onto her truck(s) on-site, ensuring timely and full

[4]Most sellers carry 1-3 trucks of vegetables to the market every day. A seller is effectively a small enterprise that may be run by a couple of individuals (Song, 2023).

delivery and payment. Prices are all free-on-board (FOB) as the buyer uses her own truck(s) to ship products and bears all the downstream shipping costs.

Competition within this marketplace seems perfect — homogeneous products, frequent transactions, large numbers of sellers and buyers, minimal barriers to entry, and minimal information costs. Standard search models, like Diamond (1989), would argue that in such a marketplace, sellers are anonymous and searched with equal probability and that there would be no memory of where favorable opportunities were found in the past (Boudreau, Cajal-Grossi and Macchiavello, 2023).

B. The Digital System

Payments and delivery of products are on-site and immediate via the market's digital trading system. The system consists of a scale and a cashier. Once a price is agreed upon for a certain quantity, the buyer and the seller weigh the products on the ground electronic scale located at the entrance of each trading hall. The weight is automatically recorded in the digital system. By the scale, the traders communicate the agreed-upon price to the staff and swipe their cards (i.e., effectively debit cards issued by the wholesale market and linked to their bank accounts) to transfer money via the cashier. Information of the transaction, including trader identifier and transaction specifics (e.g., price, volume, and time), is also immediately logged in the system from which we obtain the data for this study.

Data recorded through the digital system are accurate and complete for three reasons. First, traders lack incentives to misrepresent prices, as cash transfers are made based on the quoted price, and are unable to misreport quantities that are automatically weighed by the scale. Second, the market charges a one-time fee per truck that a trader brings on each day and charges little if any commission fee per transaction. Traders hence tend to make all instead of only some transactions via the digital system over a day in order to spread the fixed cost as thin as possible. Third, technically, once both traders come to the market, they need to rely on the ground scale to weigh the products to conduct transactions. Trading through the system is hence a must, ensuring the completeness of the data in recording the series of transactions between each buyer-seller pair during the period of interest.

C. Transaction Data

The dataset is extracted from the proprietary database stored in the digital system, which has not been released for academic use. We employ the complete set of 179,825 buyer-seller-time specific transactions of Chinese cabbage (CC) traded on this wholesale market, covering 1,440 trading days from 2016 to 2019. CC is the most traded commodity on the market by volume, sold in bulk with no packaging. Although the shelf-life of CC could be several days in retail stores, it is perishable at the wholesale stage as overnight storage is rare, leaving little concern on inter-temporal arbitrage. CC is also highly homogeneous, leaving quality differentiation largely irrelevant in our context.

The unique dataset describes each transaction by five variables: (1) date and time of the transaction (specified to the second), (2) identifiers (IDs) of the buyer and seller, (3) name of the commodity, (4) quantity traded (in kilogram or kg), and (5) price paid (in RMB/kg). The IDs of the buyer and the seller are time-invariant, unique 9-digit numbers. The transaction data are complemented by information obtained from field observations as well as interviews with traders, market administrators, and local authorities conducted in the summer and winter of 2019.

Table 1 reports summary statistics for some key variables at the trading day level. Daily volume traded on the market has a simple mean of 144,495 kg and a large variance mainly due to the seasonality of CC production. On an average day, 125 transactions are made. The average transaction size is 1,045 kg, with most sizes lying between 500 to 1,600 kg. The mean of volume-weighted average price on a day is 1.1 RMB/kg (0.2 USD/kg) with a standard deviation of 0.5. The numbers of buyers and sellers vary across seasons, too, while the ratio of the two stays around 6.3. Market concentration is low on both the buyer and seller sides, with the transaction-number weighted average Herfindahl–Hirschman index not exceeding 0.1 for sellers (mean=0.03) and not exceeding 0.03 for buyers (mean=0.01).

Table 1—Summary Statistics: Market Features

Variable	Mean	Std. Dev.	Min.	Max.
Total volume traded (kg)	144,495.00	172,165.00	56.00	918,796.00
No. transactions	124.88	130.10	1.00	512.00
Avg. transaction size (kg)	1,044.72	541.22	56.00	16,271.00
Avg. price (RMB/kg)	1.12	0.53	0.17	3.56
No. buyers	79.01	70.42	1.00	310.00
No. sellers	12.65	9.88	1.00	56.00
Buyer-seller ratio	6.28	3.38	1.00	42.00

Note: The transaction data are trimmed by removing transactions with prices in the lower and upper one percentiles in each month. Observations of these statistics are at the market-day level, and the number of observations is 1,440. Trading days are calendar days with at least one transaction of CC. *No.* means number of, and *kg* means kilogram. The buyer-seller ratio equals dividing the daily number of buyers by the daily number of sellers on the market.

Figure 1 documents the fluctuation in daily total volume traded and weighted average prices for CC. Daily volume follows an obvious seasonal pattern, with July to early November being the peak season of each year. The volume is also subject to considerable day-to-day fluctuations due to upstream weather shocks and entry/exit of sellers. Market prices display strong seasonality and daily volatility, too. Market prices tend to be relatively low during peak trading seasons.

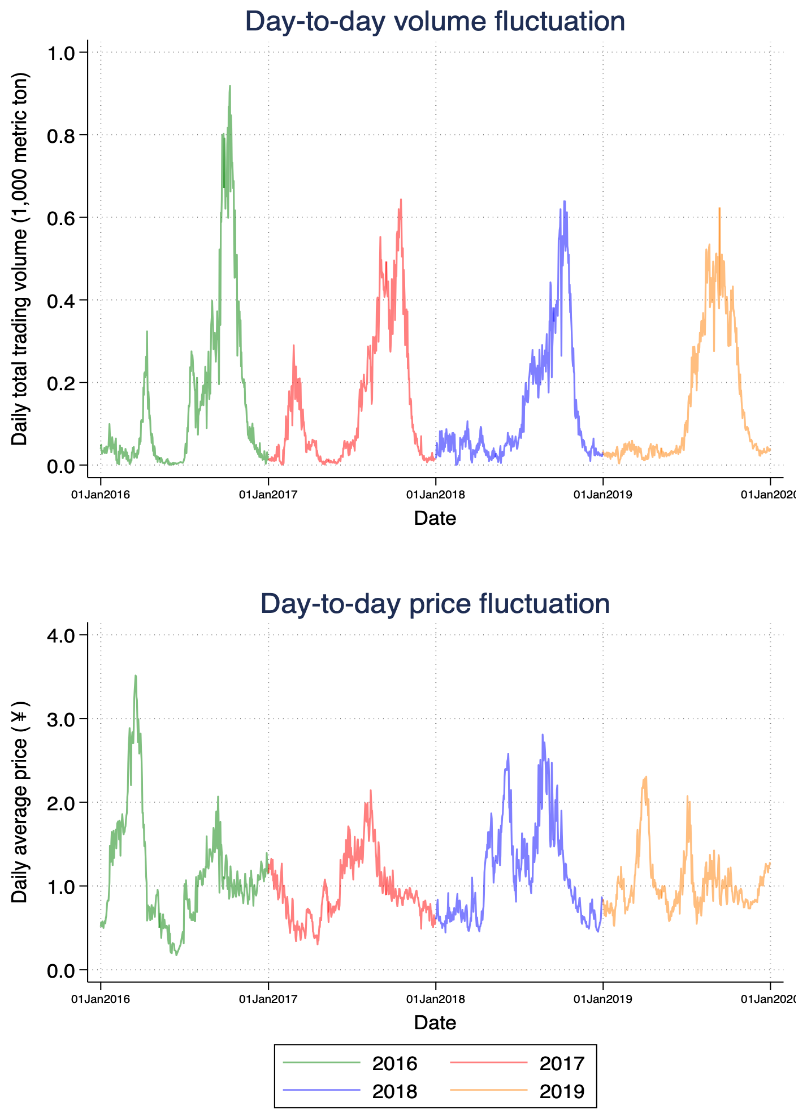

Figure 1. Day-to-day Fluctuation in Volume and Price of Chinese Cabbage

Note: The transaction data are trimmed by removing transactions with prices in the lower and upper one percentiles in each month. Real prices are used in plotting the day-to-day price fluctuation with the base month being January 2016. Consumer Price Index is obtained from the National Bureau of Statistics of China: http://www.stats.gov.cn/

Table 2 panel A reports descriptive statistics of trading activities conducted by

3,904 buyers and 1,396 sellers in the 2016-2019 dataset; the number of buyers is almost three times as large as that of sellers. On average, each buyer (seller) engages in CC trading for 11 (8) days per year. The number of visits to the market per year spans a wide range for both buyers and sellers, indicating that some are regular traders and some only come occasionally for CC. Over a year, an average buyer trades with 7 sellers, while an average seller trades with as many as 31 buyers. Within a day, though, an average buyer only purchases from one seller, while an average seller sells to 5 buyers. An average buyer (seller) procures (sells) 21 (91) tons of CC over a year with considerable heterogeneity across the traders. The largest seller sells more 4,500 tons of CC per year. An average buyer's daily purchase is 1,761 kg, and an average seller's daily sales is 7,850 kg.

Table 2—Summary Statistics: Trading Activities

Type	Variable	Mean	Std. Dev.	Min.	Max.
Panel A: All traders					
All buyers (N=3,904)	Avg. no. days present/year	11.02	24.59	1.00	234.00
	Avg. no. sellers traded/year	7.25	12.32	1.00	96.63
	Avg. no. sellers/day	1.08	0.20	1.00	4.22
	Avg. purchase/year (metric ton)	20.99	66.96	.02	1,469.31
	Avg. daily purchase (kg)	1,761.38	3,115.51	20.00	41,864.00
All sellers (N=1,396)	Avg. no. days present/year	8.00	14.49	1.00	205.00
	Avg. no. buyers traded/year	30.86	45.10	1.00	498.00
	Avg. no. buyers/day	5.28	4.09	1.00	30.86
	Avg. sales/year (metric ton)	90.52	243.69	.05	4502.01
	Avg. daily sales (kg)	7,849.90	7,172.60	50.00	44,530.29
Panel B: Frequent traders					
Freq. buyers (N=657)	Avg. no. days present/year	58.30	41.37	20.00	257.00
	Avg. no. sellers traded/year	29.92	17.39	1.00	96.63
	Avg. no. sellers/day	1.18	0.20	1.00	2.45
	Avg. purchase/year (metric ton)	109.85	141.37	1.74	1,469.31
	Avg. daily purchase (kg)	1,833.83	2,417.58	77.54	38,666.16
Freq. sellers (N=169)	Avg. no. days present/year	40.63	25.82	20.00	212.00
	Avg. no. buyers traded/year	124.61	63.56	26.00	498.00
	Avg. no. buyers/day	7.76	3.47	1.12	20.86
	Avg. sales/year (metric ton)	540.04	527.78	10.48	4,502.01
	Avg. daily sales (kg)	12,610.76	7,206.28	327.59	44,530.29

Note: Std. Dev. means standard deviation, *avg.* means average, *no.* means number of, and *kg* means kilogram. Frequent buyers/sellers transact CC for at least 20 times in a year.

D. Stylized Facts

Examining transactions of CC, two prominent traits catch attention: 1) there is considerable price dispersion within individual sellers within a day that is not explained by the volume or timing of the transactions, and 2) a large number of traders engage in repeated transactions. We further show that repeated transactions feature supply assurance for buyers.

Price Dispersion. — We find strong and persistent price dispersion across transactions. To explore the contributors to price dispersion, we decompose the variance of transaction prices to different sources and report results in Table B1. Day-to-day fluctuation of demand and supply explains half of the price variance, and seller fixed effects account for another 31.8%. The rest represents significant price dispersion "within" individual sellers on a given day (see examples of seller-day price observations in Figure A3). Transaction volume and timing only explain a small portion of the intra-seller price variance.

Figure 2 presents the distribution of the seller-day coefficient of variation (CV) in prices. Half of the seller-day CV is larger than 0.11, indicating considerable intra-seller-day price dispersion. The market hence raises an economic paradox in the sense that, the market seems vigorously competitive, yet prices for homogeneous goods are significantly dispersed for a given seller-day, an attribute not reflective of a competitive market.

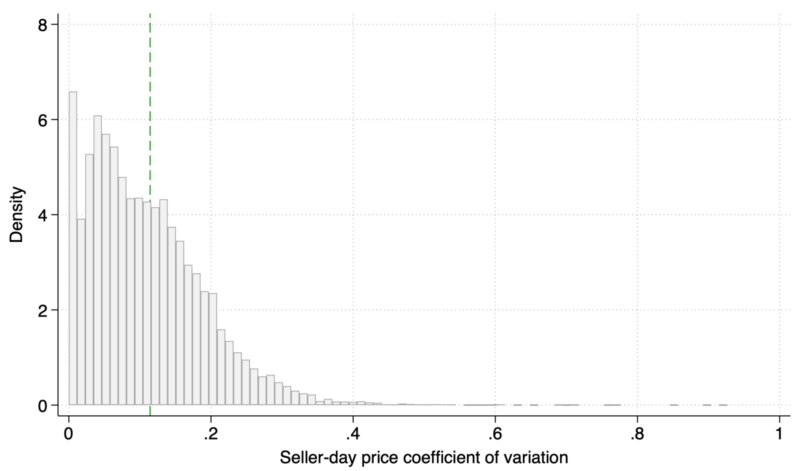

Figure 2. Distribution of Coefficient of Variation of Seller-Day Prices

Note: The coefficient of variation equals the standard deviation divided by the mean of a variable. The green line indicates the mean of the seller-day coefficient of variation, which equals 0.11.

Repeated Trade. — Browsing the transaction data, one quickly notices repeated trade: a buyer and a seller trade with each other multiple times in a year.[5] Repeated trade may reflect economic relationships between buyers and sellers,

[5]We focus on within-year instead of cross-year repeated trade because peak seasons, when most repeated trade happens, are far apart cross years as Figure 1 shows. We effectively assume that a relationship needs to be established separately, after a buyer and a seller stop trading for more than 7 months.

echoing observations from the field surveys (Song, 2023) (i.e., traders indicate that they have repeated, familiar trading "friends"). We follow the literature on economic relationships to sort out relatively *stable* repeated trade and examine its characteristics. In particular, we follow Macchiavello and Morjaria (2015) who set the threshold at 20 transactions over 20 weeks because the peak season of CC usually lasts for 4-5 months, roughly 20 weeks, too.

Table 2 panel B reports summary statistics for frequent traders who transact CC for at least 20 times (days) in a year.[6] These buyers (sellers) on average engage in CC trading for 58 (41) days per year. In a year, an average frequent buyer purchases from 30 sellers, while an average frequent seller sells to 125 buyers. Within a day, frequent buyers only purchase from one seller on average, while an average frequent seller sells to 8 buyers. The trading volume of frequent traders is much larger than the infrequent ones — an average frequent buyer (seller) procures (sells) 110 (540) tons of CC over a year. The mean of frequent buyers' daily purchases is similar (1,834 kg) to the mean purchase of infrequent buyers, but has a smaller standard deviation (2,418 kg). An average frequent seller has daily sales of 12,611 kg.

Table 3, panel A reports descriptive statistics for repeated trading pairs. In total, 541 pairs conduct repeated trade in some window of time, contributing 16.1% of CC volume traded during the four-year period. The average relationship has 34 transactions per year, ranging from 20 to 143, and trades 62,039 kg of CC in the year. On average, a pair is active on the market for 63 days in a year. That means, for more than 50% of days when both traders are on the market, they trade with each other. Within a year, an average pair lasts for 98 days (i.e., the number of days from the first transaction to the last transaction in the year), and the longest lasts for 338 days. Panel B reports the number of sellers (buyers) that a buyer (seller) repeatedly transacts with. Most buyers only have one repeated seller, while a seller has nearly six repeated buyers, echoing the large buyer-seller ratio in Table 1.

Supply Assurance. — Section II.C documents that, on each trading day, a large number of buyers compete for a pre-committed supply. Field surveys suggest that a seller almost always sells out the products by the end of the day, but a buyer may not be to procure the amount desired before a certain price above which no profits could be earned from selling to the downstream. For the buyer, the risk of being rationed is a major concern, especially for those with downstream obligations like buyers procuring on behalf of grocery stores (Song, 2023). The concern echoes the substantial fluctuation in the daily aggregate supply of CC (i.e., predominantly reflected by the daily total volume traded because CC is perishable and typically sold out on a day; see Figure 1) and in the number of

[6] Among the *infrequent* buyers (sellers), some 60% (50%) trade CC no more than twice in a year. These infrequent, spot traders generate considerable fluctuation in aggregate demand and supply in this marketplace, which we revisit in Section IV.

Table 3—Summary Statistics: Repeated Trade

Variable	No. Obs.	Mean	Std. Dev.	Min.	Max
Panel A: repeated trade					
No. trading days/year	541	33.98	16.22	20	143
Volume traded/year (kg)	541	62,039.28	57,034.94	1,554	555,920
No. days both present/year	541	62.92	31.91	21	200
Length (day)	541	98.30	72.65	21	338
Frequency (day)	541	3.22	2.49	1.00	15.50
Panel B: repeated partners					
No. repeated sellers/buyer	361	1.50	0.76	1	5
No. repeated buyers/seller	96	5.64	6.32	1	30

Note: No. means the number of, *kg* means kilogram, *length* is the number of days between the first and last transactions of a pair in a given year, and *frequency* equals the average number of days between two subsequent transactions for a given repeated pair. For a small number of pairs, there can be multiple transactions on a given day. We report here the number of days traded for each pair, instead of the number of transactions.

competing buyers relative to sellers from day to day (see Figure A2).

Supply reliability, however, is difficult to contract upon and may incentivize buyers to develop repeated or relational trade with sellers (Cajal-Grossi, Macchiavello and Noguera, 2023). To see if repeated trade provides supply assurance, we apply the method developed in Macchiavello and Morjaria (2015), constructing a reliability ratio. The ratio equals the volume of purchase of buyer i on day t ($q_{i,t}$) divided by the average volume purchased in the control period for the same buyer ($\bar{q}_{i,t}$), namely, the two weeks before t. It measures the stability of the buyer's purchase, $L_{i,t} = \frac{q_{i,t}}{\bar{q}_{i,t}}$.

A simple regression follows:

$$
\begin{aligned}
L_{i,t} =&\alpha + \beta_1 1(RT)_{i,y(t)} + \beta_2 1(RT)_{i,y(t)} \times 1(NS)_t + \beta_3 1(NS)_t \\
&+ X_{i,t}\gamma + \tau_{y(t)} + \tau_{m(t)} + \mu_i + \epsilon_{i,t},
\end{aligned}
\tag{1}
$$

where $1(RT)_{i,y(t)}$ is an indicator variable that equals one if the buyer i conducts repeated trade in the year.

Variable $1(NS)_t$ is an indicator variable that equals one if there is a negative shock in aggregate supply on day t. A negative supply shock means that the day has a total volume traded one standard deviation below a rolling average (e.g., the simple averaged daily market volumes for five days before and five days after t). The interaction term, $1(RT)_{i,y(t)} \times 1(NS)_t$, tests if buyers with repeated trade have more secured supply under negative supply shocks. The control vector, $X_{i,t}$, consists of the average price and volume per transaction in the rolling window, as well as the market average price on day t. We also add year fixed effects, $\tau_{y(t)}$, and month fixed effects, $\tau_{m(t)}$, to capture regular seasonality in the demand and supply of CC. Finally, the regression includes buyer fixed effects, μ_i, to control for time-invariant characteristics of buyers like size of the truck.

Table 4 shows that the effect of repeated trade on supply reliability is positive, suggesting that buyers who conduct repeated trade enjoy enhanced supply assurance compared to those who do not. This advantage becomes more pronounced in the face of negative supply shocks, implying that these buyers' needs are prioritized when supply is relatively scarce. Different control periods are used in constructing the reliability ratio: 10 days in columns (1) and (2), and 14 days in columns (3) and (4). For infrequent buyers (i.e., buyers who purchase CC for no less than 20 times in a year), computing the reliability ratio may not make good sense because they often do not have consecutive observations in a rolling window. To ensure that the results are not driven by infrequent buyers, we exclude them in columns (5) and (6). Similar results are obtained.

Using a stochastic frontier technique developed by Kumbhakar, Parmeter and Tsionas (2013), Appendix C further assesses whether a buyer is rationed by estimating whether the quantity *obtained* falls short of the quantity *desired* for the buyer on a day (i.e., being rationed) and how large the gap is. Table C1 shows notable reductions in the likelihood of having the gap as well as the magnitude of the gap if buyers purchase from sellers they repeatedly trade with.

Table 4—Supply Reliability Tests

Dependent variable:	Reliability Ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
RT	0.010	0.008	0.012	0.010	0.010	0.008
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Negative supply shock		-0.092		-0.088		-0.088
		(0.005)		(0.005)		(0.005)
RT × Negative supply shock		0.020		0.011		0.016
		(0.007)		(0.008)		(0.008)
No. days in rolling window	10	10	14	14	10	10
Infrequent buyers included	Y	Y	Y	Y	N	N
Year and month fixed effects	Y	Y	Y	Y	Y	Y
Buyer fixed effects	Y	Y	Y	Y	Y	Y
No. observations	163,042	163,042	163,042	163,042	149,447	149,447
Adjusted R^2	0.085	0.087	0.087	0.089	0.058	0.061

Note: Standard errors are in parentheses. *RT* indicates if the buyer conducts repeated trade in the year. The upper and lower one percentiles of the reliability ratios are dropped. In the baseline, the control period in constructing the reliability ratio is set at 10 days. We set the control period to 14 days (two weeks) and present the results in columns (3) and (4). We remove infrequent buyers who buy CC less than 20 times in a year. The results are given in columns (5) and (6).

III. Conceptual Framework

Macchiavello (2022) points out that the value of continuing relationships in deterring opportunism distinguishes *relational* trade from merely *repeated* trade.

This section outlines a conceptual model to illustrate the economic forces that sustain informal agreements between a seller and a buyer who conduct repeated transactions for the future value of their relationship. Testable hypotheses follow to help distinguish relationships sustained by the future value of continued interactions from merely repeated trade and explain how relational traders adapt to shocks.

A. Setup

Here we only highlight a few critical features of the theoretical model and present mathematical details in Appendix D. The model is characterized by 1) each seller has a pre-committed and stochastic supply over a given day of time. The supply varies due to upstream fluctuations like weather shocks; 2) the aggregate demand on a day is stochastic because the number of buyers and their demands fluctuate; 3) traders can costlessly switch between relational and spot transactions, which distinguishes from many prior models on RC; and 4) a spot buyer faces an exogenous probability of being rationed and takes as given a stochastic spot price, while a relational buyer enjoys an assured supply at a relational price.[7]

A relational buyer is one who forms an RC with a seller. In practice, a relational buyer typically calls or texts her seller and specifies a quantity desired before the transaction happens on a day, but does not pin down the price (Song, 2023). The buyer understands that the seller would charge a price floating with the real-time spot price. This pair of traders effectively prioritize each other over other trading partners and potentially interact for an indefinite number of periods $t = 1, 2, ...$ under a common time discount factor. The RC can be denoted by $C_t = \{q_t, p_t^{RC}\}_{t=1}^{\infty}$, an infinite-period agreement set by the pair in period t for current and future transactions based on the expectation of quantity q_t and price p_t^{RC}. This informal contract can be re-negotiated each period. Both traders may, of course, default in spite of their RC with a probability known to both parties.

Dynamic incentive compatibility constraints (DICCs) underpin our model and state that the traders shall not breach the RC so long as the future relationship-specific gains are sufficient to prevent opportunistic behavior (Macchiavello, 2022). For each trader, the DICC is expressed by

$$\Delta U_{t+1} \equiv U_{t+1} - U_{t+1}^{0} \geq \pi_t \tag{2}$$

where U_{t+1} denotes the present value of the payoffs from continuing the RC from

[7]It is mathematically equivalent to assume that the probability of being rationed (ϕ) is lower under RC than spot. Effectively, we normalize the ϕ under RC to be zero. Though the model is built on stylized facts observed in a wholesale vegetable market in China, the rationales help understand markets that share the key characteristics. In particular, our market of interest speaks to markets studied by a large set of theoretical and empirical research on dynamic pricing: pre-committed supply of sellers and random demand of buyers. This literature concludes that even fully flexible pricing would leave some buyers unable to fulfill desired quantities, echoing evidence of supply unreliability in Section II.D.

period $t+1$ on, U^0_{t+1} is the present value of the outside option from period $t+1$ on, the π_t is the present value of defaulting the RC in period t.

For simplicity, we assume that one failure of performing the RC leads to the termination of the relationship with probability one and the two parties conduct spot trading thereafter, which is the worst punishment and mathematically consistent with less severe punishment (Abreu, 1988). We relax this assumption in Section V.C.

It is easy to show that ΔU_{t+1} for both buyer and seller depends on the RC price agreed upon, the probability of being rationed in spot trading, the probability of default, and the time discount factor. Intuitively, ΔU_{t+1} decreases as the default probability falls and increases as traders value the future more.

B. Testable Hypotheses

Three key insights follow the conceptual model. Firstly, the value of RC relative to spot trading is offering informal supply assurance to the buyer who faces stochastic supply and a risk of being rationed. Secondly, the quasi-rent created by RC (i.e., RC surplus) and its allocation between traders depends critically on the buyer's probability of being rationed, but not on spot price in t. Thirdly, the buyer and the seller need to adjust RC terms strategically under large supply shocks to sustain the relationship. Given the insights, we propose three testable hypotheses.

Hypothesis I. — An RC has the same design as a formal contract, but lacks legal enforcement, exposing the two parties to opportunism. For the seller, the buyer could switch to spot trading to capture low prices. For the buyer, likewise, the seller may default to capture high spot prices. RC surplus is divided by the buyer and the seller to deter the opportunistic behavior of both parties.

The division of RC surplus is realized by a price premium/discount of RC transactions relative to spot transactions and determined by relative bargaining power between the buyer and the seller (Doornik, 2006). Because the risk of being rationed is on the buyer's side, the seller has all the *ex post* bargaining power and can completely expropriate the quasi-rent of RC.

Mathematically, this implies that the DICC is binding for the buyer, while the seller obtains a price premium over the spot price. The lift-hand side (LHS) of the buyer's binding DICC is the RC surplus minus discounted value of premium granted to the seller, while the right-hand side (RHS) is the net gain from default in t, namely, difference between the gain from avoiding the premium and the foregone profits due to being rationed. Intuitively, the relationship functions like an informal insurance that provides buyers with supply assurance. The buyer hence pays an *insurance premium* to the seller.

- **Hypothesis I**: *On average, buyers in relational transactions pay a premium to sellers relative to spot buyers.*

Hypothesis II. — Whether a relationship can be formed depends on if the two DICCs can be satisfied. Everything else the same, DICCs are more likely to be met with a larger RC surplus to be shared by traders. A key element of RC surplus is the risk of being rationed for the buyer, which depends on the interactions among all buyers and sellers over a buyer's presence in a year. The buyer's demand, downstream obligations, and the stochastic residual supply jointly determine the risk.

Given the market supply and number of sellers, the residual supply for a buyer decreases as the number of buyers increases or the scarcity of supply increases. The smaller the residual supply is, the higher the probability of being rationed. As the probability rises, intuitively, the quasi-rent of RC as an informal supply insurance increases. It is hence more likely that the buyer's binding DICC is satisfied, *ceteris paribus* and an RC is formed. The model, however, has little to say as to who the partner seller would be for such a buyer.

- **Hypothesis II**: *Given the market supply and the number of sellers, the more buyers competing during her presence, the more likely that a given buyer forms a relationship with a seller.*

Hypothesis III. — Relational traders adapt to changing environments by making state-contingent actions (Baker, Gibbons and Murphy, 2011). Specifically, the buyer and the seller can reallocate the RC surplus by adjusting the RC premium post a shock in market-level supply, so that DICCs continue to hold, the relationship sustains, and the joint expected payoffs are maximized.

Upon a negative shock in the aggregate supply in period t, spot prices tend to go up, *ceteris paribus*. The LHS of buyer DICC does not vary, while the RHS increases. The RHS of buyer DICC equals the gain from default (i.e., the saved premium paid to the seller) minus the loss from default (i.e., the foregone profit due to being rationed). A higher spot price means a smaller profit margin for the rationed amount of supply. The RHS would hence fall is the premium stays unchanged, inducing the buyer to default. The seller could strategically charge a lower one-time premium to maintain the binding DICC for the buyer.

Similarly, upon a positive supply shock and spot-price drop, the RHS of buyer DICC would fall if the premium in t stays unchanged. A larger premium could hence be charged while maintaining the binding DICC; the seller would leave money on the table without doing so. In both scenarios, the RC price would need to move in the same direction as the spot price does, but increases (decreases) less than the spot price does. This implies partial pass-through from spot to relational prices and reduced price fluctuation for relational traders (see Section V for discussion on the price effect of relational adaptation).

- **Hypothesis III**: *RC premium falls under a negative, market-level supply shock and rises under a positive, market-level supply shock.*

IV. Empirical Results

This section presents empirical evidence for the three hypotheses and performs a set of tests to demonstrate the robustness of the baseline results.

A. Relationships as Supply Assurance

To test Hypothesis I, we need to explain the within-seller-day price dispersion with an indicator for economic relationships. The dependent variable is the logarithm transaction price between buyer i and seller j on day t, $\ln P_{ij,t}$. The relationship dummy, $1(R)_{ij,y(t)}$ equals one if the transaction is conducted by a pair of buyer and seller who have an active relationship in year $y(t)$.

We propose two conditions for an active relationship in a given year. First, as illustrated in Section II.D, the number of transactions by a given pair in a year has to pass a threshold that is set at 20 times in the baseline (hereafter, the T threshold). Second, we construct a "trade-present" (T/P) ratio, ranging from 0 to 1, to characterize the relative fidelity of each buyer-seller pair. The ratio equals the number of transactions between a buyer and a seller in a year (T) over the number of days when both are present on the market over the year (P). By "present", we mean the buyer/seller conducts at least one active transaction on the day. A high T/P ratio indicates a high level of exclusivity of the relational partner for a trader.

Figure 3 plots the T/P ratio over the number of transactions by the pair in the year (T). Each dot represents a buyer-seller pair. Pairs with at least 20 times of mutual presence (i.e., $P \geq 20$) are included in the figure; other pairs are excluded because they do not satisfy the T threshold by construction. The vertical red line indicates the 20-time T threshold. Holding P constant, the more transactions a pair conducts in a year, the higher the T/P ratio tends to be. In the baseline estimation, 0.5 is set as the T/P threshold indicated by the horizontal blue line.

Identification. — When the T and T/P thresholds are both met, the RC indicator, $1(R)_{ij,y(t)}$ turns one in the baseline regression expressed below.

$$\ln P_{ij,t} = \alpha + \beta 1(R)_{ij,y(t)} + \theta_{j,t} + B_{i,y(t)}\eta + Z_{ij,t}\gamma + \tau_{h(t)} + \epsilon_{ij,t}, \tag{3}$$

where vector $\theta_{j,t}$ contains seller-day fixed effects to absorb unobserved seller-day characteristics that may affect prices, including the seller's pre-committed supply on the day; the remaining price variation is seller-day specific.

Vector $B_{i,y(t)}$ contains buyer characteristics in the year that potentially affect the formation of RCs and prices. The three characteristics include buyer i's average purchase volume per transaction, average time of transaction, and total number of days trading on the market, capturing features of the buyer's demand

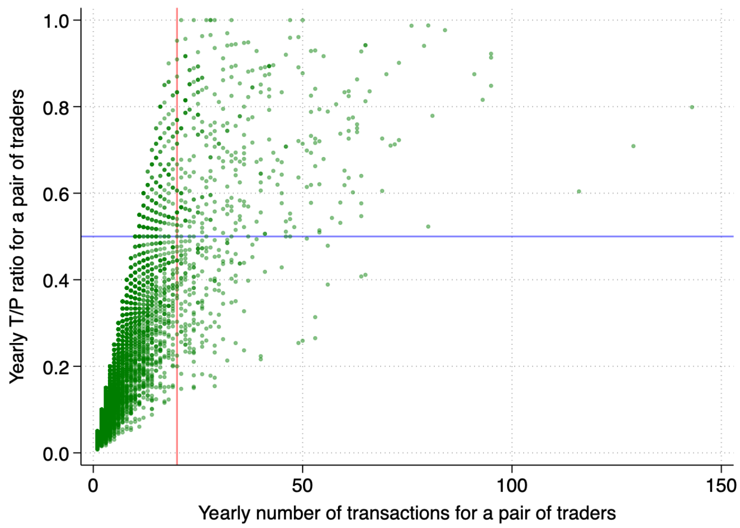

FIGURE 3. THE "TRADE-PRESENT" RATIO AND THE NUMBER OF TRANSACTIONS

Note: The T/P ratio equals the number of transactions between a buyer and a seller over the number of days when both of them are present on the market. The sample includes pairs with $P \geq 20$. The red line represents the baseline T threshold (*number of transactions by the pair* = 20) for the baseline definition of RC. The blue line indicates the baseline T/P threshold, which equals 0.5.

and her likelihood of having downstream obligations.[8]

Further, vector $Z_{ij,t}$ accounts for the volume of the transaction and the relative importance of the transaction to a trader. Specifically, $Z_{ij,t}$ includes the share of this transaction in buyer i's total purchase on day t and the share of this transaction in seller j's total sales on day t. This vector absorbs the effect of relative bargaining power of the two sides to help isolate the effect of RC. Hour fixed effects (e.g., 9-10 a.m.), $\tau_{h(t)}$, absorb the market-level hour specific price volatility when the transaction is done. Term $\epsilon_{ij,t}$ contains errors that are clustered at the seller level.

The RC is, of course, not randomly imposed on traders. This econometric regression makes an identification assumption that, controlling for observed seller-day fixed effects ($\theta_{j,t}$), buyer characteristics ($B_{i,y(t)}$), and transaction characteristics ($Z_{ij,t}$ and $\tau_{h(t)}$), no other factor simultaneously affects $1(R)_{ij,y(t)}$ and the price charged by the seller on day t; the only remaining systematic price difference between relational *versus* nomad buyers is the RC status.

The baseline estimated coefficient of the RC indicator is 0.026, which suggests an average 2.6% higher price paid by RC buyers, supporting the hypothesis that buyers under relational transactions on average pay a premium to sellers relative

[8]These characteristics can also proxy the buyer's propensity to search. See discussion on search and price dispersion in Section V.B.

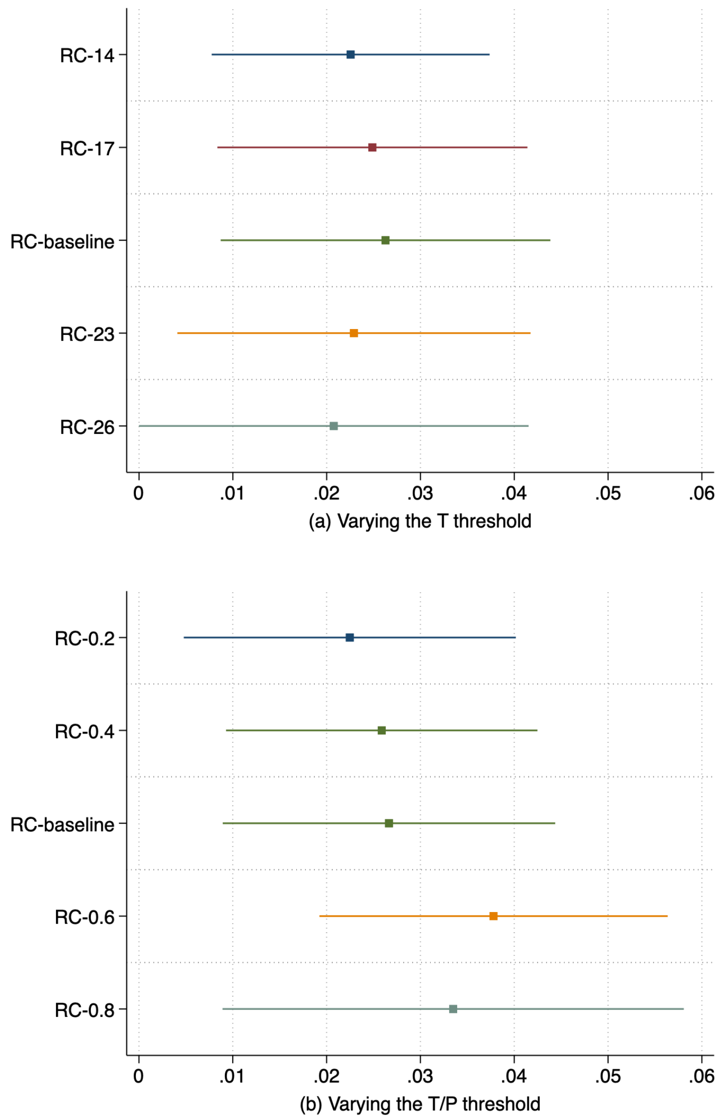

Figure 4. Estimated Price Premium Paid by Relational Buyers (Test I)

Note: In all regression estimated for Hypothesis I, we exclude seller-day observations where the seller has only non-relational or relational transactions. For those observations, the relationship indicator has no variation in identifying its price effect. The resulting sample size is 70,362 transactions. The regressions generate an adjusted $R^2 \approx 0.88$. In panel (a), we fix the T/P ratio threshold at 0.5. A relationship is active if a pair of buyer and seller trade at least T times in a year where T is specified on the vertical axis (e.g., RC-17). In panel (b), we fix the T threshold at 20 times in a year and have a T/P threshold specified on the vertical axis (e.g., RC-0.4). The point of each bar is the point estimate of the RC premium, while the bar covers the corresponding 90% confidence interval.

to prices paid by spot buyers. The estimate is statistically significant at 5% level. Given the narrow profit margins in wholesale produce trading (8-15% according to field surveys), the magnitude of this premium holds economic significance.

Robustness Checks. — To see the robustness of baseline results, we first check if the results are sensitive to the T threshold. Keeping the T/P threshold at 0.5, the upper panel of Figure 4 displays the estimated RC premium as we vary the T threshold. The point estimates are all positive and significant and suggest that a 2-3% premium is paid by relational buyers.[9]

Next, we check if the results are sensitive to the T/P threshold. The lower panel of Figure 4 plots the mean estimated RC premium when fixing the T threshold at 20 and varying the T/P ratio threshold. The estimates are again consistent with the baseline and suggest a 2-4% premium paid by relational buyers.

Finally, we remove a large number of infrequent buyers and perform the test. The new results align with the baseline. This alternative sample of observations is also employed for the other two tests discussed below. All results agree with the baseline and available upon readers' request.

B. *Forming Relationships*

Given the total supply on a day, the larger the number of competing buyers and the larger their aggregate demand, the smaller the residual supply is for buyer i. Figure A2 indicates that the number of buyers, especially spot buyers, is considerably larger in peak seasons compared with lean seasons. Peak seasons also see more sellers and larger total volumes traded each day.

To test Hypothesis II, we employ two variables to proxy the aggregate supply faced by a buyer over her presence in year y. Variable $S_{i,y}$ is the average number of sellers for buyer i per day of presence in the year, and $Mvl_{i,y}$ is the logarithm average total volume traded on the market per day of presence. These two variables describe the abundance of aggregate supply the buyer faces over her presence.

Variable $B/S_{i,y}$ is the average daily buyer-number(B)-over-seller-number(S) ratio for the buyer's presence. Given the aggregate supply, this variable effectively measures the average competitiveness among buyers for buyer i in year y and implies the buyer's residual supply. The larger $B/S_{i,y}$, the smaller residual supply tends to be, *ceteris paribus.*

The dependent variable, $1(R)_{i,y}$, equals 1 if buyer i forms an RC in the year, namely, if she trades repeatedly with at least one seller for at least 20 times in the year and the T/P ratio between them is no less than 0.5. We also include buyer-year control variables and year fixed effects. Control variables include the average

[9]The significance falls slightly as T threshold increases. It is the case likely because $1(R)_{ij,y(t)} = 0$ for some actual relationships if raising the bar of T too high, creating measurement error and noise in identifying the RC effect. The baseline threshold at $T = 20$ seems more appropriate.

daily volume purchased in the year (in logarithm form), the annual average time of trade (measured in hour-minute and in logarithm form), and the buyer's total number of days trading in the year.

Table 5 reports summary statistics for the buyer-year level observations. In the baseline, we focus on buyers who conduct at least 20 transactions in year y and hence potentially form RCs. There are 1,385 observations, and the mean $1(R)_{i,y}$ is 0.21 with a standard deviation of 0.41. That is, 21% of relatively frequent buyers form relationships in a given year. The mean of $B/S_{i,y}$ equals 7.11 with a standard deviation of 0.90.

Table 5—Summary Statistics: Forming Relationships

Variable	Mean	Std. Dev.	Min.	Max.
Buyer forms RC, 1 if yes	0.21	0.41	0	1
Buyer's avg. no. sellers (S)	21.60	5.32	2.39	33.97
Buyer's avg. market volume (Mvl)	313.65	111.45	21.95	729.19
Buyer's avg. buyer-seller ratio (B/S)	7.11	0.90	2.46	16.19
Buyer's no. trading days	68.39	50.53	20	311
Buyer's avg. volume purchased	1.76	1.95	0.07	38.67
Buyer's avg. trading time	3.10	0.73	1.62	5.44

Note: The sample size is 1,385. *Buyer's no. trading days* is the number of trading days for a buyer in a given year. *Buyer's avg. purchase* is the average volume purchased for a buyer in a year. *Buyer's avg. trading time* is the average hour-minute when the first transaction of a day happens for a buyer in a year. Volume is measured in 1,000 kg.

Estimation results from the probit model are reported in Table 6. The likelihood ratio χ^2 is large with a $Prob > \chi^2$ approximately zero, indicating a good fit and high statistical power of the model. Variable $B/S_{i,y}$ has a positive and significant coefficient estimated. The partial effect of $B/S_{i,y}$ at its mean equals 0.07 with a standard error of 0.01. The partial effect implies that, when $B/S_{i,y}$ increases by one standard deviation, the buyer's probability of forming an RC increases by 0.06 or $\frac{0.07\times0.90}{0.21} = 29\%$ of the mean $1(R)_{i,y}$, which is economically significant.

The table also shows that buyers, who encounter a smaller average volume available, visit the market more frequently, or acquire a larger average volume, are more likely to form an RC. This makes intuitive sense because a buyer with more frequent visits is more likely to have downstream obligations, and a larger buyer or a buyer facing smaller residual supply tends to experience a larger risk of being rationed, resulting in a larger quasi-rent from RC, *ceteris paribus*.

We further examine the dynamic process of forming relationships by examining newly formed RCs in our sample. Some buyers start trading in the wholesale market as spot buyers and gradually establish relationships with certain sellers. We find that these buyers experience statistically more negative supply shocks and smaller average supply per buyer before and in the early stage of RC formation.

Relatively small residual supply in this period again implies a relatively large risk of being rationed for the buyers. The larger risk likely offers a stronger incentive for the buyers to build relationships. For more details, please see Appendix F.

TABLE 6—PROBIT REGRESSION ON RELATIONSHIP FORMATION (TEST II)

Variable	Coefficient	Std. Err.	z	P> |z|
Buyer's avg. no. sellers (S)	0.054	0.028	1.90	0.058
Buyer's avg. market volume (Mvl)	-0.919	0.322	-2.86	0.004
Buyer's avg. buyer-seller ratio (B/S)	0.326	0.063	5.19	0.000
Buyer's no. trading days	0.013	0.001	12.51	0.000
Buyer's avg. volume purchased	0.347	0.058	5.97	0.000
Buyer's avg. trading time	-0.409	0.209	-1.96	0.050
Year fixed effects	Yes			
No. observations	1,385			
Log likelihood	-528.01			
Likelihood ratio χ^2	362.72			
$Prob > \chi^2$	0.00			

Note: Buyer's no. trading days is the number of trading days for a buyer in a given year. *Buyer's avg. purchase* is the average volume purchased for a buyer in a year. *Buyer's avg. trading time* is the average hour-minute when the first transaction of a day happens for a buyer in a year.

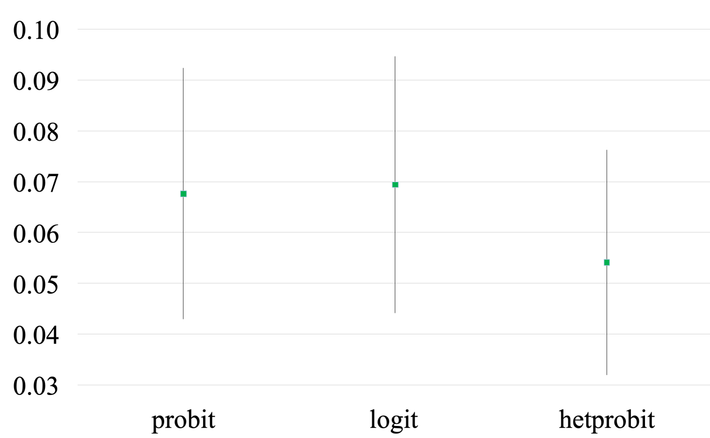

FIGURE 5. ESTIMATED PARTIAL EFFECTS AT MEAN B/S RATIO (TEST II)

Note: The three bars report the estimated partial effects of the buyer-seller ratio at its mean for probit, logit, and heteroskedastic probit models, respectively. The point on each bar is the point estimate of partial effect, while the bar covers the corresponding 95% confidence interval.

Robustness Checks. — The logit model produces partial effect estimates for $B/S_{i,y}$ and other variables that are consistent with the baseline. Due to concerns about heteroskedasticity in the latent error term in the probit model, we estimate a heteroskedastic probit model suggested by Wooldridge (2010). The estimated partial effect for $B/S_{i,y}$ has a mean of 0.05 with a standard error of 0.01, which again aligns with baseline estimates. The partial effect estimates generated by the probit, logit, and heteroskedastic probit models are summarized in Figure 5 and consistent in the sign, the magnitude, and the confidence interval. Besides, we use the buyer's annual total volume purchased as a control variable instead of the buyer's average daily volume purchased in robustness test, again obtaining consistent results.

A buyer's presence may be endogenous to her decision on forming RC. Some unobserved characteristics of the buyer may affect her presence at the marketplace, and are at the same time correlated with her RC status. To address this concern, we replace the RHS variables $S_{i,y}$, $Mvl_{i,y}$, and $B/S_{i,y}$ by $S_{i,pre}$, $Mvl_{i,pre}$, and $B/S_{i,pre}$, where the subscript *pre* indicates the period when i's first relationship has not yet be established.[10] During this period, we think that the buyer is conceptualizing the market condition. Market condition experienced by the buyer during this period affects her RC formation decision only through affecting the her expectation of key parameters in the model, such as ϕ_b. The test results are consistent with the baseline with an amplified magnitude, and are available upon request.

C. *Relational Adaptation to Changing Market Conditions*

To test Hypotheses III, we interact the relationship dummy with the supply-shock dummies to equation 3. The main identifying variation that we leverage comes from large, stochastic, and exogenous fluctuations in supply relative to the smooth bi-weekly trend. The supply fluctuations could be caused by weather shocks on farms, road conditions, and other exogenous factors that are unlikely anticipated, let alone affected, by traders on the wholesale market and hence not incorporated in the terms of RC.

As is in Section II.D, days with supply shocks are defined as those when the market's total volume traded significantly deviates from its rolling average. Specifically, days with volume sales one standard deviation below the two-week rolling average are classified as days with negative supply shocks, whereas days with volume sales one standard deviation above the rolling average are considered days with positive supply shocks. The positive (negative) shock indicator is denoted $1(PS)_t$ ($1(NS)_t$). Focusing on sufficiently large supply swings mitigates noise in RC price and RC premium driven by minor non-price variables in equation (D12)

[10]We cannot know when the relationship is formally established in the buyer's perception. To be consistent with our baseline definition of RC, we use a 20 cutoff here, i.e., the 20th transaction between i and j mark the establishment of their relationship. We also try a 10 and 15 cutoff and obtain consistent results.

Table 7—Relational Price and Premium under Supply Shocks (Test III)

	(1)	(2)	(3)	(4)	(5)
Dependent variable			log(transaction price)		
RC-baseline	0.027				
	(0.011)				
RC-14		0.028			
		(0.009)			
RC-17			0.029		
			(0.010)		
RC-23				0.023	
				(0.012)	
RC-26					0.020
					(0.013)
Positive shock	-0.054	-0.055	-0.054	-0.054	-0.053
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Negative shock	0.112	0.112	0.112	0.111	0.111
	(0.012)	(0.011)	(0.011)	(0.012)	(0.012)
RC-baseline × Positive shock	0.014				
	(0.008)				
RC-14 × Positive shock		0.019			
		(0.007)			
RC-17 × Positive shock			0.018		
			(0.008)		
RC-23 × Positive shock				0.014	
				(0.008)	
RC-26 × Positive shock					0.013
					(0.008)
RC-baseline × Negative shock	-0.066				
	(0.026)				
RC-14 × Negative shock		-0.055			
		(0.025)			
RC-17 × Negative shock			-0.063		
			(0.026)		
RC-23 × Negative shock				-0.066	
				(0.026)	
RC-26 × Negative shock					-0.070
					(0.025)
Control variables	Yes	Yes	Yes	Yes	Yes
Seller-Month fixed effects	Yes	Yes	Yes	Yes	Yes
Hour fixed effects	Yes	Yes	Yes	Yes	Yes
No. observations	179,825	179,825	179,825	179,825	179,825
R^2	0.717	0.717	0.717	0.717	0.717

Note: Standard errors are clustered at the seller level and shown in parentheses. "RC-n" means a relationship is defined if the number of trades between the buyer and the seller exceeds n in a year, and the T/P ratio is no less than 0.5. Shocks are defined in Section IV.C.

in Appendix D.

Following equation 3, the econometric model is specified as

$$
\begin{aligned}
\ln P_{ij,t} = & \\
& \alpha + \beta_1 \, R_{ij,y(t)} + \beta_2 1(PS)_t + \beta_3 1(NS)_t \\
& + \beta_4 \, R_{ij,y(t)} \times 1(PS)_t + \beta_5 \, R_{ij,y(t)} \times 1(NS)_t \\
& + \theta_{j,m(t)} + B_{i,y(t)}\eta + Z_{ij,t}\gamma + \tau_{h(t)} + \epsilon_{ij,t},
\end{aligned}
\tag{4}
$$

As we already include day-to-day shock indicators, we include seller-month fixed effects, $\theta_{j,m(t)}$, instead of seller-day fixed effects in equation 4. The error term, $\epsilon_{ij,t}$, is again clustered at the seller level.

Estimation results are reported in column (1) of Table 7. When there is a positive (negative) supply shock, the average spot price decreases (increases) by $\hat{\beta}_2 = 0.054$ ($\hat{\beta}_3 = 0.112$) or 5.4% (11.2%), which are economically significant swings. The normal-time RC premium is 2.7% indicated by $\hat{\beta}_1$.

Changes in the RC premium under shocks are indicated by $\hat{\beta}_1 + \hat{\beta}_4$ and $\hat{\beta}_1 + \hat{\beta}_5$ in equation 4. In the presence of a positive supply shock, the RC premium rises to 4.1% and is significant. Conversely, under a negative supply shock, the RC premium declines to -3.9% and is statistically indistinguishable from zero. Compared with the premium of 2.7% in normal times, the RC premium is suppressed under a negative supply shock and boosted under a positive supply shock, varying in the opposite direction as the spot price and supporting Hypothesis III.

The changes in RC premium are achieved by partial pass-through from spot to RC prices. To confirm this, we check RC prices under positive (negative) shocks by reading $\hat{\beta}_2 + \hat{\beta}_4$ ($\hat{\beta}_3 + \hat{\beta}_5$). As the spot price varies, RC prices change in the same direction. Specifically, when there is a positive (negative) supply shock, the average RC price decreases (increases) by 4.0% (5.6%). The results indicate that RC price tends to be *stickier* than the spot price. In this sense, RCs also serve as a *cushion* that buffers large price swings for relational traders. We offer more discussion on this in Section V.

Robustness Checks. — Columns (2) through (5) in Table 7 report results of varying the T threshold in testing Hypotheses III. The results align with the estimates reported in column (1). Table G3 reports results on Hypotheses III by varying the T/P ratio threshold. All estimates align with the baseline results in signs and magnitudes. Consistent results are also obtained if varying the number of days used to calculate the rolling average and define supply shocks (see Table G4). We drop the T/P ratio threshold in defining RC, while keeping the T threshold as prior studies do (Macchiavello and Morjaria, 2015). The results are consistent and reported in Table G5.

To conclude, we have provided compelling evidence that repeated trade in the market signify relational adaptation to fluctuating circumstances in this marketplace.The value of forming relationships as informal quantity insurance to buyers is evident by the estimated price premium paid by relational buyers. We then show that relationships are more likely to be formed if buyers face smaller residual supply during presence. The adjustments in contractual terms (RC premium) after the realization of market-level supply swings are in the directions predicted by theory and can strategically sustain RCs for maximized joint expected payoffs.

V. Discussion

We discuss a few extensions of the model and consider alternative explanations for the test results presented so far. Additionally, we explore factors driving strategic defaults and termination of relationships.

A. Model Extensions

Up to this point, our focus has been on the risk of being rationed from the buyer's perspective, and let the buyer whose DICC is binding decide whether to build relationships. This setup aligns with the stylized facts documented in Section II, the fact that each buyer typically trades with only one seller a day, and the fact that buyer fixed effects explain two thirds of variation in $1(RC)_{ij,t}$. See pages 19-22 in (Cajal-Grossi, Macchiavello and Noguera, 2023) for similar discussion on conceptualizing relationships from the buyer perspective.

In reality, there are occasions where a seller faces a risk of not being able to sell all his pre-committed supply above a certain price. For instance, one seller interviewed mentioned that he would approach his *long-standing* customers at the end of the day, asking if they could buy up his unsold products (Song, 2023). This practice underscores the seller-side concern about being rationed and how relational buyers provide demand assurance.

Denoting the buyer-side risk of being rationed by ϕ^b and the seller-side risk by ϕ^s, one can easily show that, as long as $\phi^s < \phi^b$, normalizing $\phi^s = 0$ leads to the same insights derived in the baseline model. If $\phi^s > \phi^b$, instead, our model would characterize a relationship that provides demand assurance, instead of supply assurance, and suggest that a *price discount* would be offered by the seller to relational buyers relative to spot buyers. Morton (2024), for instance, shows empirical evidence for a price discount offered by garment buyers in India to their relational suppliers because RC provides demand assurance. Our empirical results in Section IV.A, however, suggest the relative importance of supply assurance in this context because a price premium is empirically identified for RC transactions.

Beyond the partial equilibrium effects of RC, a natural follow-up question is how forming relationships affects spot traders and aggregate supply assurance as well as market-level price volatility. Regarding aggregate supply assurance, it is straightforward to see that only *marginal* relational buyers — buyers who would like to form relationships, but have not yet done so — would suffer a higher probability of being rationed due to one more established RC. Buyers who do not have downstream obligations are not subject to being rationed (see Appendix D).

The *marginal* relational buyers suffer because their residual supply is reduced by adding RCs because sellers effectively move supply *ordered* by relational buyers out of total supply. Whether the aggregate supply assurance increases or decreases depends mainly on the relative size of active and *marginal* relational buyers as well as the strength of established relationships.

In detecting the aggregate price fluctuation effect, constructing a structural general equilibrium model is required, which falls beyond the scope of this article. Darmouni, Aberg and Tolvanen (2023) present a framework that provides insights pertinent to our context. The authors model formal quantity contracts and spot trade for the pulp and paper industry. Like CC, pulp is a homogeneous good, but traded under different prices across buyer-seller pairs in a given period. Their structural framework shows that the quantity contracts could increase or decrease the aggregate price dispersion on the market. Intuitively, spot traders experience more price volatility and dispersion, while relational traders enjoy reduced price fluctuation. The net change depends on the relative numbers of spot and relational traders.

B. *Alternative Explanations*

We now discuss alternative reasons for repeated trade or price dispersion in a market of homogeneous goods and alternative drivers for developing RCs. In the trade literature, a firm makes frequent and small purchases of durable goods with an exporter instead of a lump-sum purchase to avoid high upfront costs associated with a lumpy order, especially if the firm faces a credit constraint Zhang (2023). In our context of perishable products, however, repeated small purchases over several days are not equivalent to a lump-sum purchase on one day. More importantly, even the largest lumpy purchase is small in our context because even the value of one full truckload of cabbage is only worth some $1,500, which buyers easily afford.

Search and price discrimination could lead to heterogeneous prices paid by buyers of homogeneous goods. Marshall (2020), for instance, uses a sequential-search model to show that buyers with relatively high search costs and low propensity to search would be charged higher prices by a given seller. Two observations in the market of interest suggest that search and price discrimination do not explain the price dispersion we observe. First, search costs are minimal for each buyer because, on average, there are only 12-13 sellers per day, and a buyer can easily walk up to them and negotiate (see a scene of the market in Figure A1).[11] Second, price discrimination implies that buyers with downstream obligations, who tend to search more to meet target quantities, would receive lower prices than other buyers. Buyers with downstream obligations are most likely relational buyers

[11]We also run a robustness test by excluding observations on days with no more than 5 sellers (i.e., days with relatively high market concentration) and obtain consistent results with Table 7. This indicates that the baseline outcomes are not sensitive to how hard search tends to be on a day.

in our context and pay prices higher than spot buyers, which contradicts what the search model predicts (see why relational buyers tend to have downstream obligations in Appendix D).

We explain why credit provision, timely delivery or payment, and quality information are of little relevance given the institutional features of our setup in Section II.A. One other potential driver for developing RCs is to reduce price volatility in transactions. In Appendix E, we show that price volatility in repeated transactions is noticeably lower than that in spot transactions. This aligns with the implication of Hypothesis III in Section III.B that RC prices only partially adjust to swings in spot prices driven by supply shocks in a given period, resulting in higher price stability compared against spot trading. However, it does not imply that relationships are established with the primary goal of reducing price volatility. As mentioned, field interviews suggest that buyers typically call or text their relational sellers before transactions occur, specifying a quantity but not the price (Song, 2023). Both parties understand that the actual price will be floating with the equilibrium spot price revealed later. The RC is effectively an informal quantity contract, akin to those seen in various other industries, such as garment and pulp and paper (Cajal-Grossi, Macchiavello and Noguera, 2023; Darmouni, Aberg and Tolvanen, 2023).

Besides securing supply, *ordering* an amount in advance provides the relational buyer with a relatively flexible arrival time. That is, relational buyers can arrive at their convenience with less worry about the supply running out. A simple t-test suggests that spot buyers tend to arrive/leave earlier compared to buyers who have established RCs, but the difference is statistically insignificant. We also perform a t-test on the standard deviation of the arrival/leave time for relational *versus* spot buyers. We find that the former exhibits a smaller standard deviation, suggesting less flexible arrival time of relational buyers. This evidence suggests that the desire for a more flexible trading window is unlikely the key incentive for building relationships, either. In fact, the test result echoes Appendix D, which suggests that relational buyers tend to be those with downstream obligations and hence may need to complete transactions within a relatively narrow window in order to deliver target quantities of goods to their downstream buyers timely.

C. Strategic Defaults and Relationship Termination

In Section IV.C, we show that RC terms are adjusted under market-wide supply shocks to deter parties from behaving opportunistically, so that the relationship is sustained and the value of continuing the relationship is retained. However, not all relationships are sustained under shocks. When the spot price deviates so much from the mean, it is not hard to see that DICCs may not simultaneously hold. In such cases, an RC is strategically defaulted.

The empirical challenge in detecting opportunistic behavior stems from the difficulty in distinguishing strategic defaults from unwilling defaults. Unwilling defaults occur, when the defaulting party genuinely cannot comply with their obligations or promises due to, for instance, a shortage of supply to sellers (Blouin and Macchiavello, 2019). Of course, even an unwilling deviation from the agreement could harm the relationship. For example, the buyer would have a lower expectation of the relationship's value in providing supply assurance for her if the seller does not show up on some business days.

Our dataset has an advantage in studying strategic defaults. It encompasses all transactions of all traders on the market, enabling us to identify instances where buyers and sellers in a relationship do not trade with each other despite both being present on a given day. To distinguish defaults driven by necessity from those with strategic intent, we set the baseline condition: buyer i and seller j each conduct at least one transaction on day t, but they do not transact with each other.

A dummy variable, $Default_{ij,t}$, equals one if the baseline condition is met and zero otherwise. Its sample mean is 0.031 and standard deviation is 0.174. We use a *probit* model to examine the drivers of strategic defaults. Informed by the literature, we use three sets of drivers: 1) market conditions on t, including the number of sellers, the buyer-seller ratio, and supply shocks; 2) measures of the relationship's relative intensity, including the average fraction of buyer's purchase out of the seller's sales and the average fraction of seller's sales out of the buyer's purchase in the previous month; and 3) the history of defaults, measured as the cumulative number of defaults up to day t.[12] We further add year and month fixed effects. Two control variables are used, including the cumulative number of relational transactions for the pair by t (Macchiavello and Morjaria (2015) call this variable age of the RC) and the market concentration of seller sales.

Results are reported in Table 8. The buyer-seller ratio is a significant predictor, and a higher buyer-seller ratio would increase the likelihood of default. The partial effect at the mean ratio is 0.003 with a standard error of 0.001, implying a $\frac{0.003\times 2.82}{0.03} = 23\%$ increase from the mean default probability as the ratio increases by one standard deviation. Intuitively, given the number of sellers, a higher buyer-seller ratio implies intensified competition among buyers. This is likely to drive up the spot price, creating a stronger incentive for sellers to default and capture a higher spot price instead of maintaining the RC. In the meantime, a larger number of sellers and a positive supply shock may induce defaults because buyers have better outside options facing abundant supply and are incentivized to default in order to capture lower spot prices.

Buyers' purchase share and sellers' sales share are significant predictors for defaults, too. A higher RC intensity can indicate a higher value of the relationship by reducing the expected likelihood of default. The findings echo Weisbuch, Kirman and Herreiner (2000) and Blouin and Macchiavello (2019) who show that

[12]Considering the history of default challenges our assumption in Section III that a default ceases a relationship. We make this assumption to simplify the theoretical illustration. We could relax the assumption by following Levin (2003), who shows that allowing an RC to restore after a default does not change the RC terms as long as one party pays a lump sum to compensate the other party for the lost RC surplus due to the default.

the more valuable a relationship, the smaller the risk of strategic defaults.

Finally, the history of defaults is a significant predictor. A larger number of past defaults results in a higher probability of another default in t. Intuitively, both parties tend to value the relationship less if they have experienced a larger number of defaults in the past and are likely to default again. In our conceptual model, a larger number of past defaults could translate to a larger expected likelihood of default and reduce the RC surplus.

Table 8—Probit Regression on Strategic Default

Variable	Coefficient	Std. Err.	z	$P > \|z\|$
No. sellers	0.026	0.003	7.40	0.000
Buyer/seller ratio	0.033	0.015	2.18	0.029
Positive shock	-0.209	0.089	-2.36	0.018
Negative shock	-0.048	0.104	-0.46	0.646
Avg. purchase share last month	-1.213	0.089	-13.63	0.000
Avg. sales share last month	-0.244	0.125	-1.95	0.051
No. past defaults	0.023	0.002	10.36	0.000
Year and month fixed effects	Yes			
No. observations	9,512			
Log likelihood	-1,123.27			
Likelihood ratio χ^2	492.74			
$Prob > \chi^2$	0.00			

Note: The buyer-seller ratio is computed by dividing the number of buyers by the number of sellers on the market on day t. Supply shocks are defined in Section II.D.

One concern may arise: even if both traders are present on the market, a seller may simply have insufficient supply to meet the buyer's demand, potentially leading to the under-counting of unwilling defaults and the over-counting of strategic defaults. To address this concern, we add a second condition to identify strategic defaults — at the time of buyer i's arrival (using the time of i's first transaction as proxy), seller j still has a sufficient stock to meet i's revealed quantity demanded. While this condition helps exclude unwilling defaults, it may also exclude some strategic defaults because not reserving quantity for a relational buyer until her arrival can be a sign of strategic default in itself. Nevertheless, similar results of the probit regression are obtained and shown in Table G6. Additionally, we estimate a logit model and a heteroskedastic probit model, yielding similar results available upon request.

To further illustrate, we examine the dynamic process of relationship termination by examining newly ended relationships in our sample. The key finding is that the breakup pairs experience statistically more positive supply shocks and a larger average supply per buyer in the few months before the final breakup. The relatively abundant market supply in the these months implies a relatively small risk of being rationed for buyers and hence a lower RC surplus. This echoes our discussion in Section IV.B on the incentive to form RC.

VI. Concluding Remarks

We provide novel empirical evidence on relational adaptation alongside active spot trading. The study is situated in one of the largest wholesale vegetable markets in Asia. Our analysis commences by showing that 1) prices on the market exhibit persistent dispersion, even at the seller-day level, 2) a large number of buyers and sellers engage in repeated transactions, and 3) buyers who engage in repeated trade enjoy more reliable supply both in regular market conditions and during substantial market-level supply drops.

The facts are integrated into a conceptual model that characterizes repeated trade as a relational contract between a seller and a buyer amidst a marketplace with active and competitive spot trading. The model posits that, if the repeated trade is indeed relational, buyers pay their relational sellers a price premium in exchange for a more secure supply. The relational surplus is allocated towards the party experiencing less uncertainty (i.e., the sellers), leaving the participation constraint for the buyers binding. The model further predicts that relational traders adapt to random shocks to sustain the relationship and achieve higher joint expected payoffs — the RC premium varies in the opposite direction with spot prices under market-level supply shocks.

All the hypotheses are supported by empirical tests. Relational contracting is shown to be an effective way of reducing supply uncertainty, and relational adaptation helps traders maximize expected joint payoffs facing frequent demand and supply fluctuation, prominent and widespread features of agricultural supply chains. These empirical findings are robust to alternative definitions of relationships and supply shocks as well as alternative econometric models.

Indeed, with growing odds of extreme events worldwide and across industries (Hadachek, Ma and Sexton, 2024), supply disruptions are becoming a common and serious concern for many supply chains (Grossman, Helpman and Lhuillier, 2023). Arm's-length spot transactions among firms alone may not be sufficient to address this issue. We highlight the value of constantly adapt to changing market conditions *ex post* via relational contracting — providing more stability in supply to relational buyers and generating higher joint expected payoffs for relational traders than spot adaptation would.

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Additional Statistics

This appendix section provides additional information on the marketplace and the repeated transactions observed in the dataset.

Figure A1 provides a glimpse into a typical scene at the market. The market has multiple trading halls. Inside this particular trading hall, sellers display stacks of white radishes on the ground in front of their cold storage trucks. All buyers are free to walk around and talk with sellers. There are no restrictions as to the price settled, quantity purchased, or the number of sellers a buyer may talk to or negotiate with.

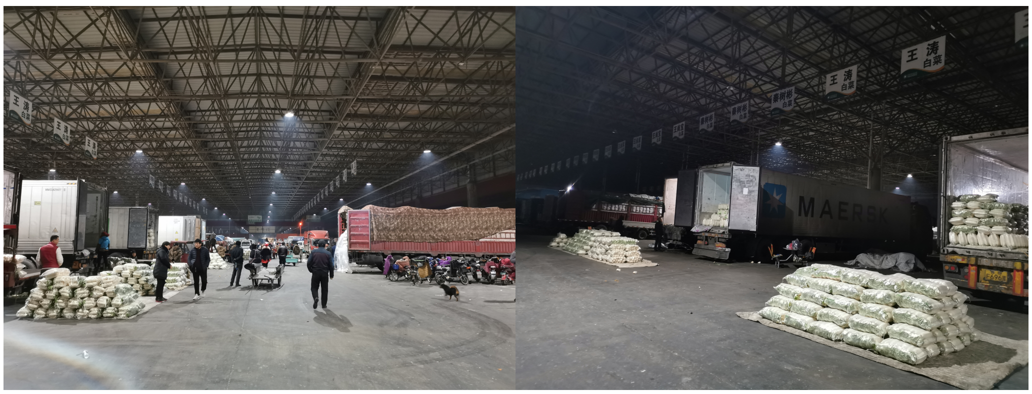

Figure A1. Scenes of the Wholesale Vegetable Market

Note: The pictures were taken by the authors on December 17, 2019.

Similar to market volume traded and prices (see Figure 1), there is considerable fluctuation in the numbers of buyers and sellers trading on the market of CC. Figure A2 reports the day-to-day fluctuation. Specifically, the number of buyers, especially spot buyers, varies positively with the market volume traded, reflecting increased market activity during peak trading season. In the meantime, the number of sellers exhibits similar seasonal variation.

The corresponding buyer-seller number ratio is always larger than 1.0, suggesting that there are always more buyers than sellers on the market. Additionally, this ratio stays mostly in the range of 5 to 10, displaying weaker and different seasonality compared to the number of buyers. The ratio also exhibits considerable day-to-day fluctuations. The varying buyer-seller ratio may indicate a varying probability of being rationed for buyers on the market, which we discuss in detail in Appendix D.

In addition to day-to-day price fluctuation shown in Figure 1, there is considerable intra-seller-day price dispersion. Figure A3 plots prices charged by several sellers over a particular trading day, with the green line representing the hourly

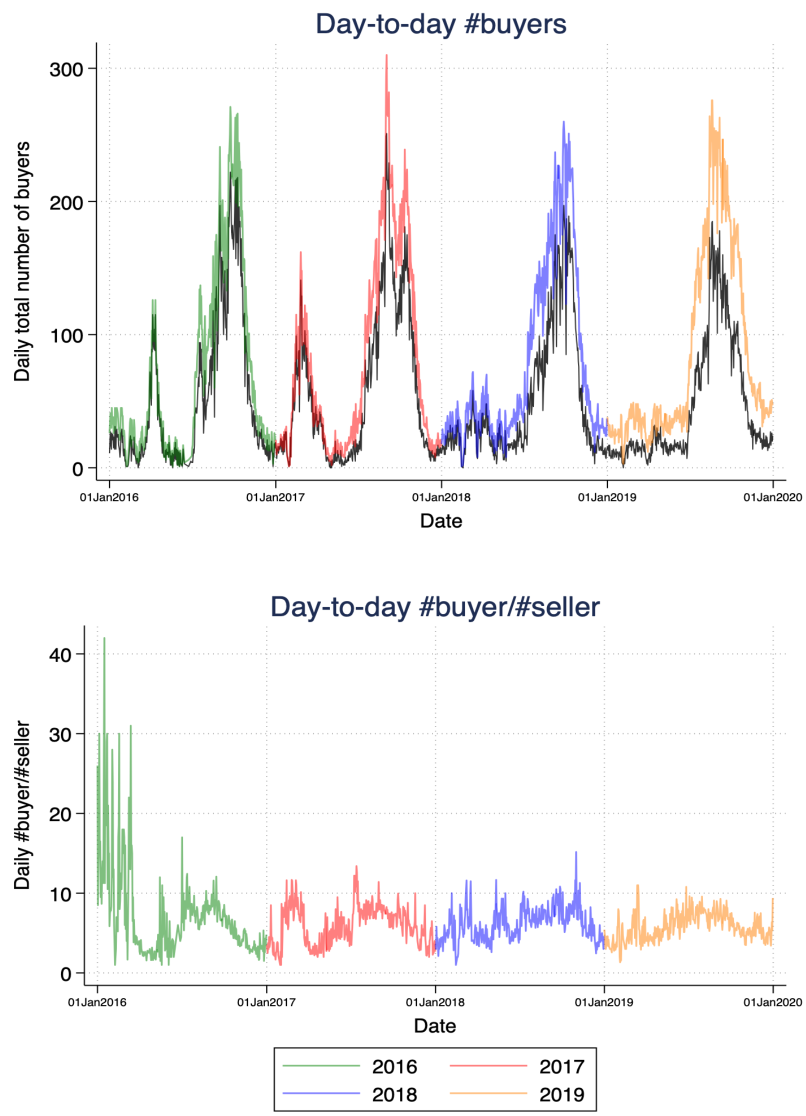

FIGURE A2. DAY-TO-DAY FLUCTUATION IN THE NUMBER OF BUYERS AND BUYER-SELLER RATIO

Note: The solid black curve in the upper panel represents the number of nomad buyers on the market on a given day, while the colored curves depict the number of all buyers. Nomad buyers are buyers who do not conduct repeated trade in a year. Repeated trade is defined as a pair of traders trading at least 20 times in a year, following the baseline definition outlined in Section II.D. The buyer-seller ratio is computed by dividing the daily number of buyers by the daily number of sellers on the market of CC.

weighted average market price for that day and the size of each circle corresponding to the relative size of the transaction at the given price. Transaction time and

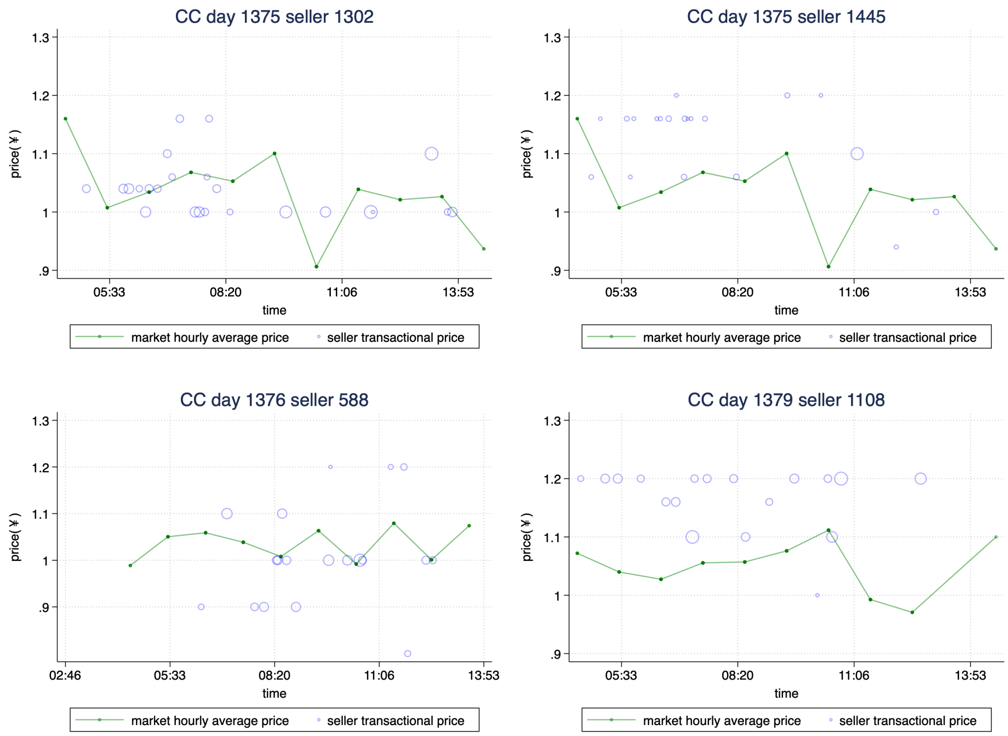

Figure A3. Examples of Seller-Day Price Dispersion

Note: The green line represents hourly weighted average price of the market for the given day. The size of each circle corresponds to the relative size of the transaction at the given price.

volume do not seem to explain much of the price dispersion we observe.

Upon examination of all seller-day plots, it becomes evident that within-seller price dispersion persists across sellers and trading days and cannot be fully attributed to trading time and volume.[13] As is shown in Section IV.A, repeated transactions explain the within-seller price dispersion to a significant extent.

Variance Decomposition

We employ the STATA ANOVA command to assess how much variance in transaction prices can be explained by the trading day, transaction timing, volume traded, and seller identifier. ANOVA essentially conducts a fixed-effect regression decomposition of variance in the dependent variable.

Table B1 presents the outcomes obtained from ANOVA for the full dataset. Trading day and seller identifier explain most of the variance. The key takeaway

[13]Interested readers may request to see the complete set of seller-day price plots.

is that seller fixed effects, along with volume and the timing of transactions, explain 84% of the price variance on the market; considerable price dispersion remains within a seller on a given day.

Table B1—Variance Decomposition of Transaction Prices

Years	Source	Seq. Sum Sq.	Dof	Mean Sq.	F	Prob>F
2016-2019	Model sum sq.	39160.47	9182	4.26	106.34	0.00
	Seller identifier	14633.54	1394	10.50	261.75	0.00
	Day of trade	23200.15	1439	16.12	402.00	0.00
	Volume traded	1234.62	6326	0.20	4.87	0.00
	Hour of trade	92.16	23	4.01	99.91	0.00
	Residual sum sq.	6843.56	170641	0.04		
	Total sum sq.	46004.02	179823	0.26		
	No. observations	179,824				
	Adjusted R^2	0.84				

Note: Dof means the degree of freedom. F stands for the test statistic for the F-test. *Volume traded* is the quantity traded measured in kg. *Trading hour* is the indicator for the specific hour of a day when the transaction occurs, for instance, during 9-10 a.m.

Zero Inefficiency Stochastic Frontier Estimation

We test, for each buyer, whether and by how much she is rationed upon each transaction. In other words, we check whether the buyer is able to purchase the amount she wants and if not, how much less. Being rationed less means the buyer enjoys a higher degree of supply assurance.

We employ a stochastic frontier technique. The classic Stochastic Frontier Model (SFM) assumes that a firm has a production function $f(z_i, \beta)$ and would produce $q_i = f(z_i, \beta)$ in a world without error or inefficiency, yet potentially produces less than it might due to inefficiency. When adapted to the estimation of buyers' demand function, the degree of rationing corresponds to the degree of inefficiency in the production SFM.

We begin by specifying a constant elasticity, stochastic desired volume of purchase function,

$$Q_{i,t} = p_{i,t}^{\gamma} exp(\alpha_i + Z_{i,t}\beta + \upsilon_{i,t}) \tag{C1}$$

where $p_{i,t}$ is the price that buyer i faces on day t,[14]. Variable $\upsilon_{i,t}$ is independent, identically, and normally distributed with a support of $N(0, \sigma_\upsilon^2)$. It captures the

[14]For buyers who paid multiple prices on a day, $p_{i,t}$ is the lowest price i paid. The logic is that if i is not rationed, she should be able to purchase $q_{i,t}(p_{i,t})$ at the lowest price $p_{i,t}$.

effects of unobservable characteristics and measurement errors. The vector $Z_{i,t}$ includes controls for month to capture seasonality in demand, and day-of-week because buyers' downstream obligations may vary by day-of-week.

The buyer's actual amount of purchase is expressed as

$$q_{i,t} = \xi_{i,t} p_{i,t}^{\gamma} exp(\alpha_i + Z_{i,t}\beta + \upsilon_{i,t}) \tag{C2}$$

where $\xi_{i,t}$ is a random variable between 0 and 1 and indicates the degree of being rationed.

A logarithmic transformation of equation (C2) yields a linear equation,

$$\ln q_{i,t} = \alpha_i + Z_{i,t}\beta + \gamma p_{i,t} + \upsilon_{i,t} + \ln \xi_{i,t} \tag{C3}$$

Let $u_{i,t} = -\ln(\xi_{i,t})$, we have

$$\ln q_{i,t} = \alpha_i + Z_{i,t}\beta + \gamma p_{i,t} + \upsilon_{i,t} - u_{i,t} \tag{C4}$$

It is implausible to assume that buyers are rationed every day on the market of our interest. In fact, they may purchase according to their demand for a good number of days. The notable limitation of using the standard SFM is its assumption that each observation lies within the efficiency frontier, namely, there is some degree of inefficiency (rationing) associated with each purchase. Thus, the standard SFM cannot accommodate cases where certain observations are efficient (i.e., not subject to rationing).

To address this limitation of SFM in our context, we use the Zero Inefficiency Stochastic Frontier (ZIFS) model to perform the estimations. Introduced by Kumbhakar, Parmeter and Tsionas (2013), ZISF is a modification of the standard SFM that allows both fully efficient and inefficient observations in the sample. Specifically, ZISF allows zero inefficiencies by allowing the inefficiency term, $u_{i,t}$, to be zero for some t and $u_{i,t} = 0$ for others. In our context, the ZISF helps assess which regime, being rationed or not rationed, each buyer-day observation belongs to.

Suppose that buyer i is rationed with probability $1 - \rho_i$ and not rationed with probability ρ_i. The composed error term is $\upsilon_{i,t} - u_{i,t}(1 - 1\{u_{i,t} = 0\})$. The idiosyncratic component, $\upsilon_{i,t}$, is assumed to be independent, identically, and normally distributed with the support of $N(0, \sigma_{\upsilon_i})$ over all observation days. The inefficiency term, $u_{i,t}$, is specified to be independent and identically distributed with a half-normal support, $N^+(0, \sigma_{u_i}^2)$.

For each individual buyer i, we perform the estimation on i's time series of purchases $q_{i,t}$, $t = 1, 2, ..., T_i$ where T_i is specific to buyer i. We restrict the estimation to the sub-sample of buyers with $T_i >= 200$, totaling 162 buyers.[15]

[15] In Kumbhakar, Parmeter and Tsionas (2013), the statistical reliability of the model is validated when the number of observations is larger than 200. The model is validated under this condition because the

The estimation generates day-specific posterior probabilities of being rationed for each t, $1-\check{\rho}_{i,t}$

$$1-\check{\rho}_{i,t}=1-\frac{(\hat{\rho}/\hat{\sigma}_v)\phi(\hat{\varepsilon}_t/\hat{\sigma}_v)}{(\hat{\rho}/\hat{\sigma}_v)\phi(\hat{\varepsilon}_t/\hat{\sigma}_v)+((1-\hat{\rho}))\frac{2}{\hat{\sigma}}\phi(\hat{\varepsilon}_t/\hat{\sigma})\Phi(-\hat{\varepsilon}_t/\hat{\sigma}_0)} \tag{C5}$$

where $\sigma=\sigma_v^2+\sigma_u^2$, $\sigma_0=\sigma_u/\sigma_v\sigma$.

Let $\hat{u}_{i,t}$ be the conditional mean estimator for u developed by Jondrow et al. (1982) and is referred to as the Jondrow inefficiency score (henceforth, ZI-JLMS).

$$\hat{u}_{i,t}=(1-\hat{\rho})\frac{\hat{\sigma}_u^2}{\hat{\sigma}_u^2+\hat{\sigma}_v^2}[\hat{\sigma_0}\frac{\phi(\hat{\varepsilon}_t/\hat{\sigma}_0)}{\phi(-\hat{\varepsilon}_t/\hat{\sigma}_0)}-\hat{\varepsilon}_t] \tag{C6}$$

For brevity, all subscription i on the right-hand side (RHS) of this equation is omitted.

The magnitude of being rationed can be computed by multiplying the inefficiency score $\hat{u}_{i,t}$ with the probability $1-\check{\rho}_{i,t}$:

$$\hat{r}_{i,t}=(1-\check{\rho}_{i,t})\hat{u}_{i,t} \tag{C7}$$

Alternatively, we can censor the inefficiency scores as follows

- $\check{\rho}_{i,t}\geq 0.95$: i is not rationed on t (zero inefficiency)
- $\check{\rho}_{i,t}<0.95$: i is rationed on t and receives a ZI-JLMS inefficiency score

Following Kumbhakar, Parmeter and Tsionas (2013), we employ three measures of being rationed. First, the JLMS inefficiency scores $\hat{u}_{i,t}$ alone can be used to indicate the degree of being rationed for each purchase. Second, $\hat{r}_{i,t}$ gives the magnitude of being rationed by incorporating the probability of being rationed. Third, the censored ZI-JLMS scores can be used to measure if the buyer is being rationed and by how much.[16] As a robustness check, we adjust the censoring threshold to 0.90 instead of 0.95 as in the baseline.

Having obtained these rationing measures, we proceed to test if conducting repeated trade could reduce the likelihood and/or magnitude of being rationed for buyers. To do so, we first identify buyers who conduct repeated trade in a year to be those who have traded with a seller for at least 20 times in the year. We use a dummy variable $1(RT)_{i,t}$ to indicate if buyer i trades with her repeated seller on day t. Note that for buyers who do not conduct repeated trade, $1(RT)_{i,t}=0$ for all t in a given year. We regress the three rationing measures on $1(RT)_{i,t}$. Year

performance of the pseudo-likelihood ratio statistic appears to follow closely the asymptotic distribution.

[16]In Kumbhakar, Parmeter and Tsionas (2013), all of the three measures of inefficiency are used in the empirical example. The authors point out that how one chooses to measure inefficiency has an impact on the shape of the distribution of conditional inefficiency without asserting which one is better.

fixed effects and buyer characteristics (i.e., the ones specified in Section IV.A) are added as control variables.

The final sub-sample includes 93 *RT* buyer(-year)s and 100 non-*RT* buyer(-year)s. Table C1 reports the results and suggests that buyers conducting repeated trade tend to be rationed significantly less, however being rationed is measured. [17] The effect is economically significant, too. For instance, the coefficient of *RT* is -0.05, when the censored JLMS are used to measure rationing. Given that the censored JLMS has a standard deviation of 0.21, the reduction in the probability of being rationed if a buyer opts for her repeated seller corresponds to as much as one-fourth of the standard deviation.

Table C1—Repeated Trade Provides Supply Assurance (ZISF Test)

	(1)	(2)	(3)	(4)
Rationing measure	JMLS	(1-ρ)$\times$JLMS	Censored JLMS Cutoff=0.95	Censored JLMS Cutoff=0.90
RT	-0.052	-0.041	-0.050	-0.052
	(0.025)	(0.020)	(0.023)	(0.020)
Year fixed effects	Y	Y	Y	Y
Buyer characteristics	Y	Y	Y	Y
No. observations	44,457	44,457	44,457	44,457
No. clusters	444	444	444	444

Note: *RT* indicates if the buyer trades with her repeated seller on the day. Standard errors are bootstrapped with clusters at the buyer-year level and shown in parentheses. Columns (1)-(4) employ different measures for the probability and degree of being rationed. Buyer characteristics include buyer's average purchase volume per transaction in a given year, average time of transaction in the year, and total number of days trading on the market in the year.

A Conceptual Model on Relational Contracts

We first explain why the risk of being rationed is relevant in our context and set up a conceptual model that incorporates all the stylized facts documented in Section II.

D1. Rationing with Constrained Demand

Being rationed (i.e., facing supply insecurity) is a major concern for buyers in the marketplace of interest. At first glance, the concern might be surprising: given that the market is competitive, traders search at minimal costs, and each

[17] The statistical identification of ρ_i requires observations of non-rationed days, which is a valid assumption in our context as long as the buyers are not rationed on some days of the data period. As a robustness check, we further trim the sub-sample by excluding buyers for whom $\rho_{i,t} < 0.90$ for all t in a year. The results of the same set of regressions are consistent with the baseline results and available upon request.

pair of traders freely negotiate price and quantity, one would expect that each buyer should be able to obtain any quantity demanded at a given price along her demand curve, rendering rationing irrelevant in the context.

To see why being rationed remains a key concern for at least some buyers in this well-functioning and competitive market, it's essential to highlight a few key features of the market. 1) The commodity traded, Chinese cabbage, is highly perishable; the commodity value falls drastically by the end of each trading day, and there is little overnight storage (i.e., a fixed and short trading window). 2) During a trading day, each seller comes to the market with a fixed quantity that varies due to random shocks in the upstream market (i.e., the seller has a pre-committed and stochastic supply). 3) Each seller faces stochastic arrival of buyers with heterogeneous demand throughout the day (i.e., uncertain demand). 4) Prices are not posted but negotiated by each pair of traders for each transaction and are freely adjusted based on market dynamics.

The first three features listed above make our market highly comparable to seasonal goods markets (e.g., Christmas gifts) and markets for goods with a fixed supply (e.g., airlines) that employ complex inter-temporal pricing strategies to avoid stock-outs as well as unsold units. Extensive research on dynamic pricing has been conducted in the context of these markets (Carlton, 1978; Deneckere and Peck, 2012; Williams, 2022). The studies demonstrate that, due to pre-committed supply and uncertain demand, even with freely adjustable prices over the trading window, some buyers may fail to fulfill their demand. Similarly, some sellers may fail to sell out their inventory. The finding aligns with observations of unfilled flight cabins and passengers unable to secure desired flight seats from day to day. In our context, buyers not fulfilling their demand would be referred to as being rationed or suffering supply insecurity.

This strand of literature, however, typically assumes posted prices and often oligopolistic competition, which does not align with our case. Does the same finding of buyers being rationed still apply in a competitive market with individually negotiated prices?

A fifth feature of the wholesale vegetable market needs to be highlighted to explain the rationale for supply insecurity. Buyers procuring a commodity in the primary wholesale market need to sell the purchased commodity to downstream buyers to make profits. Field surveys inform us that their downstream buyers could be secondary wholesale markets, grocery stores, restaurants, government canteens, etc. (see Section II.A).

Thus, the demand of a buyer is jointly constrained by her daily shipping capacity and downstream market conditions. We use a simple figure to demonstrate the constrained demand of a buyer and deliver the economic intuition as to why the buyer may be rationed.

In Figure D1, the residual market supply curve for the buyer is denoted by S_t for day t and is determined by the supply and demand of other buyers. Under negative (positive) supply shocks, the residual market supply curve shifts to S_t^-

(S_t^+).

The demand curve for buyer i is downward sloping and kinked at three points. First, the buyer has a fixed shipping capacity on the day, say a truck, and can procure no more than $q_{i,t}^{max}$ no matter how low the price falls. There is thus no shortage of supply for the buyer given prices below p^{low}.

Second, the buyer purchases between $\bar{q_{i,t}}$ to $q_{i,t}^{max}$ for prices between p^{low} and $p^D - \tau(q)$. Here $p^D - \tau(q)$ is the price that buyer i receives from its downstream buyers net of the unit shipping cost, and $\bar{q_{i,t}}$ represents an obligation with downstream buyers. For instance, a buyer selling to grocery stores, restaurants, and government canteens often has a target quantity of supply (with some flexibility denoted by $q_{i,t}^{max}$ -$\bar{q_{i,t}}$) to fulfill at each visit and a pre-negotiated price to receive. Within this segment of demand, there is also no shortage of supply from the buyer's perspective.

Third, as price rises higher than $p^D - \tau(q)$, the buyer incurs a loss for each unit procured. The buyer might still buy some units due to reputation concerns. Specifically, not meeting a target quantity to supply, $\bar{q_{i,t}}$, harms the buyer's reputation in the downstream market, and the decreased goodwill translates to profit losses in future periods (Matsa, 2011). The buyer hence buys the commodity with a larger demand elasticity and stops buying when the negotiated price is so high that the loss per unit outweighs the reputation saved per unit or $r(q)$.

For prices between $p^D - \tau(q)$ and $p^D - \tau(q) + r(q)$, the quantity rationed equals the difference between the target quantity $\bar{q_{i,t}}$ and the quantity purchased $q_{i,t}^*$.[18] For equilibrium prices higher than $p^D - \tau(q) + r(q)$, the quantity rationed is as large as $\bar{q_{i,t}}$.

Not all buyers are concerned with being rationed. For instance, buyers selling to secondary-stage markets may find a target quantity of supply or reputation less relevant.[19] Figure D1, lower panel demonstrates the alternative scenario. The buyer again has a fixed shipping capacity of $q_{i,t}^{max}$ and expects to sell units purchased at p^D to the downstream market on a given day. Thus, $p^D - \tau(q)$ is the highest price that buyer i is willing to pay to ensure non-negative profits. Below $p^D - \tau(q)$, there is again no supply shortage from the buyer's perspective.

At $p^D - \tau(q)$, the buyer would be willing to buy $q'_{i,t}$ and make no profits. At this price, however, the sellers might only be willing to sell a quantity $q_{i,t}^*$ when the residual market supply is low (e.g., the supply curve is S_t^-; supply under a negative shock). The wedge between $q'_{i,t}$ and the quantity purchased $q_{i,t}^*$ has an interpretation different from $\Delta q_{i,t}$ in Figure D1, upper panel. This is because no amount between $q'_{i,t}$ and $q_{i,t}^{max}$ is an obligation from the buyer's perspective. The

[18] Setting $\bar{q_{i,t}}$ at a price lower than $p^D - \tau(q)$ would result in a greater shortage of supply at a given residual supply. This adjustment would strengthen the key intuition.

[19] Based on our field interviews, these buyers may as well have a target quantity to procure, especially if they have relational buyers in the downstream market or simply want to fill their trucks. If so, we should model their demand in a similar way as in the first scenario discussed.

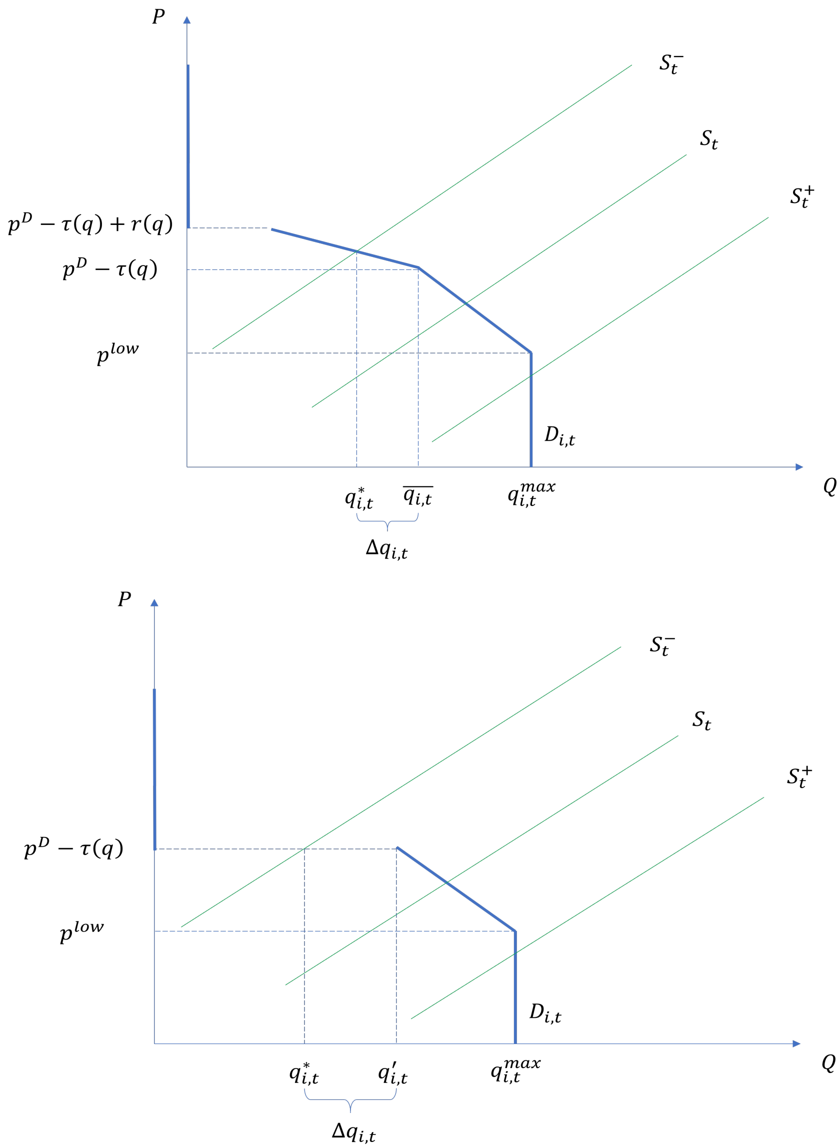

FIGURE D1. QUANTITY RATIONED FOR A CONSTRAINED DEMAND AND A COMPETITIVE MARKET

Note: Authors' creation.

wedge hence does not mean that the buyer is rationed.[20]

[20]The unit shipping cost likely falls in the quantity shipped due to non-trivial fixed costs of shipping via trucks. Thus, the buyer may not buy any quantity smaller than $q'_{i,t}$ at $p^D - \tau(q)$ because a larger $\tau(q)$ occurs for a smaller q and hence a loss. If the buyer does not buy anything, the profit is zero.

The probability and degree of being rationed for a given buyer are determined by the distribution of the residual supply, as suggested in Figure D1. The residual supply is the supply remaining after accounting for the portions captured by other buyers on the market. Given the total supply, the residual supply for a buyer typically diminishes as the number of competing buyers increases and their combined demand rises.

In summary, being rationed in a competitive market is theoretically possible and empirically salient in our context where a seller's supply is pre-determined and stochastic, the demand he faces is random, and the demand of buyers is constrained by downstream conditions and obligations. The buyer demand is not a smooth and complete downward-sloping curve, but a curve with kinks and breaks due to the buyer's fixed shipping capacity and a finite downstream price to receive. A quantity rationed can hence be defined as the difference between the quantity demanded and quantity procured from the market. Buyers with downstream obligations lose profits if rationed, providing them an incentive to form relationships to ensure a stable supply from sellers and avoid profit losses.

D2. Relational Contracts

Given the setup described in Section III, we provide mathematical details here. Determined by market supply and demand in period t, the spot market price is also volatile and denoted by p_t. Assume that the spot market price falls in a distribution that is common knowledge to traders. The buyer (b) and the seller (s) can trade on the spot market at p_t.

In each period, the buyer purchases q_t units of a vegetable from the seller, subsequently selling it to a downstream buyer at an exogenous price of p^D, net of transport costs. Given that there are on average 6 times as many buyers as sellers on a day (see Table 1), we assume that the daily supply of a seller can cover any q_t that a buyer may ask for. The seller procures from upstream farmers at price p^U. The upstream and downstream prices are considered fixed so that volatility in this market is highlighted.

The buyer and the seller may form an RC and potentially interact for an indefinite number of periods $t = 1, 2, ...$ under a common time discount factor, $0 < \delta < 1$. The RC can be denoted by $C_t = \{q_t, p_t^{RC}\}_{t=1}^{\infty}$, an infinite-period agreement set by the pair of traders in period t for current and future transactions based on the expectation.

Because transactions feature on-site cash and good transfers (see Section II.A), we consider no risk in deferred payment or delivery. For simplicity, we normalize the quantity traded, q_t, to 1.0. We abstract from haggling and let the price quote be a take-it-or-leave-it offer made by the seller as in Antras and Foley (2015). The RHS of DICC is straightforward to construct. If the RC is breached in t, the buyer buys from the spot market and faces a rate of being rationed (i.e., a portion of q_t not fulfilled), $0 < \phi^b < 1$.

The net return from default for the buyer in t is

$$(p^D - p_t)(1 - \phi^b) - (p^D - p_t^{RC}). \tag{D1}$$

The net return from default for the seller in t is

$$-p_t^{RC} + p_t. \tag{D2}$$

The default returns for buyer and seller add up to $-(p^D - p_t)\phi^b$.

The LHS of DICC captures the expected difference between continuing the RC and staying on the spot market from period $t+1$ and on. For the buyer, it is

$$b : U_{t+1}^{b0} = (p^D - \bar{p})(1 - \phi^b)\frac{\delta}{1-\delta}, \tag{D3}$$

where $\bar{p}$ is the expected spot market price, and for the seller, we have

$$s : U_{t+1}^{s0} = (\bar{p} - p^U)\frac{\delta}{1-\delta}. \tag{D4}$$

We define variable μ_t as the expected probability that the RC is executed in any period after t, which is updated after each period and an increasing function of the accumulative transactions under the RC, in the spirit of Macchiavello and Morjaria (2015). Without additional information about the future, we assume that the buyer and seller expect some normal-time p^{RC} for all post-t periods and expect spot market prices at $\bar{p}$ in future periods, the mean of the spot price distribution. Assume that the expectation of p_t^{RC} is simply p^{RC} just like the expectation of p_t is $\bar{p}$.

The total discounted payoff under the RC in all periods from $t+1$ on is denoted by U_{t+1}^b (U_{t+1}^s) for the buyer (seller) and expressed in equation (D5).

$$\begin{aligned} U_{t+1}^b &= \sum_{\tau=1}^{\infty}(p^D - p^{RC})\mu_t\delta^\tau \\ &+ \sum_{\tau=1}^{\infty}\mu_t^{\tau-1}(1-\mu_t)\delta^\tau[(p^D - \bar{p})(1-\phi^b) + \sum_{T=1}^{\infty}(p^D - \bar{p})(1-\phi^b)\delta^T] \\ &= (p^D - p^{RC})\frac{\mu_t\delta}{1-\mu_t\delta} + (p^D - \bar{p})(1-\phi^b)\frac{\delta}{1-\delta}\frac{1-\mu_t}{1-\mu_t\delta}. \end{aligned} \tag{D5}$$

We hence express the LHS of DICC for buyer b as

$$\begin{aligned}\Delta U_{t+1}^{b} &= (p^{D} - p^{RC})\frac{\mu_t \delta}{1-\mu_t\delta} - (p^{D} - \bar{p})(1-\phi^{b})\frac{\delta}{1-\delta}\frac{\mu_t(1-\delta)}{1-\mu_t\delta} \\ &= [(p^{D} - \bar{p})\phi^{b} - (p^{RC} - \bar{p})]\frac{\mu_t\delta}{1-\mu_t\delta}.\end{aligned} \tag{D6}$$

Similarly, the LHS of DICC for the seller s is

$$\Delta U_{t+1}^{s} = (p^{RC} - \bar{p})\frac{\mu_t\delta}{1-\mu_t\delta}. \tag{D7}$$

The sum of these two terms equals the net aggregate surplus of continuing RC in period t. Note that the RC surplus does not vary with the spot price in any period or the normal-time RC price and increases in ϕ^{b}, leading to Hypothesis II in Section III.[21]

$$\Delta S_{t+1} = (p^{D} - \bar{p})\phi^{b}\frac{\mu_t\delta}{1-\mu_t\delta}. \tag{D8}$$

We now derive the other two hypotheses based on the DICCs. Recall that the seller obtains the rest of the RC surplus, leaving expression (D7) no less than expression (D2). The mathematical meaning is that

$$(p^{RC} - \bar{p})\frac{\mu_t\delta}{1-\mu_t\delta} > -p_t^{RC} + p_t. \tag{D9}$$

Taking expectation on both sides, inequality D9 suggests that

$$p^{RC} > \bar{p}. \tag{D10}$$

This result leads to Hypothesis I. In practice, p^{RC} is typically specified as some percentage/portion higher than $\bar{p}$ by the relational traders.

The DICC for the buyer is binding, namely, expression (D6) equalizes expression (D1). Mathematically, the binding buyer DICC implies

$$\Delta U_{t+1}^{b} = (p^{D} - p_t)(1-\phi^{b}) - (p^{D} - p_t^{RC}). \tag{D11}$$

[21] ΔS_{t+1}^{s} is positive as long as $p^{D} > \bar{p}$. Given that the sum of RHS terms is $-(p^{D} - p_t)\phi^{b}$, this seems to suggest that an RC is always better than spot market trading for the two parties as long as the downstream price is higher than the spot market price in t. If the buyer and seller can find a way to split the return, they should always be able to stay in the RC. Of course, if there is a nontrivial fixed cost for establishing an RC (Cajal-Grossi, Macchiavello and Noguera, 2023), the sum of LHS would not be not necessarily larger than the sum of RHS for the first RC transaction. Thus, not every buyer would form an RC in this market. Also, recall that Appendix D.D1 demonstrates that ϕ^{b} is zero for buyers without downstream obligations. For those buyers, the value of an RC is also zero, so they are not incentivized to develop relationships.

Recall that equation (D6) is effectively ΔS_{t+1} minus $(p^{RC} - \bar{p})\frac{\mu_t \delta}{1-\mu_t \delta}$ or RC surplus minus the portion of surplus allocated to the seller. The surplus allocated to buyer does not depend on spot price in t but the expectation for transactions from $t+1$ to infinity.

To see how changes in p_t affects p_t^{RC}, rewrite equation (D11) as

$$\Delta U_{t+1}^b = (p_t^{RC} - p_t) - (p^D - p_t)\phi^b, \tag{D12}$$

where the first term is the saved cost from default (i.e., gain from default), and the second term is the foregone profit due to being rationed on the spot market (i.e., cost of default).

Under a negative supply shock, the spot price rises. The RHS of equality (D11) increases if the premium remains unchanged. The two parties may renegotiate to restore the binding DICC by reducing the one-time premium $p_t^{RC} - p_t$. Similarly, under a positive supply shock, the spot price rises. The RHS of equality (D11) decreases if the premium remains unchanged. The DICC can be restored by raising the one-time premium $p_t^{RC} - p_t$.

Intuitively, when the spot price rises, the foregone profit from default drops for the buyer because the profit margin on the spot market narrows. A smaller magnitude of the saved cost is hence required to maintain the binding DICC for the buyer. If the seller insists a normal-time premium, the buyer would default strategically as the LHS of equality (D11) falls below its RHS. Shrinking $p_t^{RC} - p_t$ is realized by not increasing p_t^{RC} as much as p_t.

Similarly, when the spot price drops, the cost of default rises for the buyer. A larger premium can be charged while maintaining the binding DICC; the seller would leave money on the table if he continues to charge a normal-time premium. Raising $p_t^{RC} - p_t$ is realized by not decreasing p_t^{RC} as much as p_t.

Price Volatility under Repeated Transactions

Section III.B suggests that spot market price fluctuation partially passes through to RC prices. Intuitively, this is because p_t^{RC} is formed based on the expected spot market price, which is stable, and stochastic day-to-day price fluctuation.

To test if prices are indeed less volatile in repeated transactions than spot market prices, we construct a volatility ratio, $vol_{ij,t}$, defined as the change in inter-day pairwise transaction price, $P_{ij,t} - P_{ij,t-1}$, divided by the change in weighted average market price, $\bar{P}_t - \bar{P}_{t-1}$.

$$vol_{ij,t} = \frac{P_{ij,t} - P_{ij,t-1}}{\bar{P}_t - \bar{P}_{t-1}} \tag{E1}$$

The ratio reflects the volatility in pairwise trade relative to the market average fluctuation. If the ratio of pair ij equals one on day t, the pair is experiencing the same volatility as the market. A ratio smaller than one indicates that the pair is experiencing a smaller price change, thus less volatility, and *vice versa*.

To construct the ratio, we first identify pairwise consecutive transactions in the dataset, namely, we select pairs that have transactions for at least two consecutive days and pull out all consecutive transactions of these pairs. We then calculate the change in the transaction price from $t-1$ to t. To ensure that the comparison is valid, we need a substantial share of repeated/relationship-based transactions. In the sub-sample, 42.4% of transactions are repeated/relationship-based, which is a significant portion.

We estimate the following equation

$$vol_{ij,t} = \beta\ 1(R)_{ij,y(t)} + \tau_{y(t)} + \tau_{m(t)} + \epsilon_{ij,t} \tag{E2}$$

where notation and variable definitions follow equation 3.[22]

If price volatility is suppressed for parties that conduct repeated trade, one would expect the coefficient of the relationship dummy to be negative. The coefficient of the RC indicator is -0.05, indicating that repeated trade indeed reduces price volatility for the buyer and seller.

Forming and Terminating Relationships

On the market of interest, buyers and sellers are free to build relationships with each other. Forming relationships must solve the credibility and clarity problems, so that a mutually beneficial long-term equilibrium can be found in a repeated game (Gibbons et al., 2021). Via a dynamic process, the two parties interact, learn, and adapt to establish an efficient relationship (Chassang, 2010). Empirical insights into the formation of relationships are scarce since we often only observe established relationships, not the formation process. Some laboratory experiments examine cooperative relationships between parties, finding that communication helps cooperation. Moreover, principle-based agreements, as opposed to rule-based ones, help relational traders achieve efficient adaptation under shocks (Gibbons et al., 2021).

On the other hand, relationships may be terminated due to defaults and other forms of poor contractual performance. The existing work on relationship termination is predominantly theoretical, too, perhaps due to limited data. Vanneste and Frank (2014), for instance, characterize termination as a function of the relationship's contractible values, non-contractible values, and outside options. Levin (2003) points out that if the buyer may manipulate the subjective performance measure, termination of a relationship may be a necessary device to create incentives for the two parties and part of the optimal contract.

[22]When computing the volatility ratios, we exclude days when the market price change is smaller than 5% to mitigate noise in the data. We then trim the ratios by excluding the lower and upper one percentiles to eliminate outliers. The number of observations is 27,261.

To examine the formation and termination of relationships in our context, we identify them as follows. In a given year, we define the first month of an active relationship, m^*, as the month when the pair's within-month T/P ratio first reaches 0.5. If we observe the pair's months before m^* with a monthly T/P ratio smaller than 0.3 and a monthly $P \geq 5$, we find a newly formed RC. This definition covers two sub-scenarios. One, the T/P ratio is small but positive before m^*, which implies a gradual process of building the relationship. Two, the T/P ratio is zero before m^* despite that the two were both present for a significant number of times, implying a rapid establishment of the relationship.

Regarding breakups, similarly, we first find the last month a relationship is active, month m_* when the pair's within-month T/P ratio is at least 0.5. If we observe that months after m_* to have a monthly T/P ratio smaller than 0.3 and monthly $P \geq 5$, we find a terminated RC. This definition also covers sub-scenarios of gradual and rapid termination of relationships.

Under the definitions, we identify 44 (66) pairs that form (terminate) relationships during the window of interest. Table F1 reports a set of t-tests on key variables for newly formed and terminated relationships. While the sample is too small for sophisticated econometric models, a few statistics of these pairs unveil intriguing patterns that align with the central economic rationale discussed earlier.

Table F1—T-Tests on Newly Formed and Terminated Relationships

Panel A: new RC	*Earlier months*		*Form months*			
	Mean	SD	Mean	SD	t-stat	$P(\lvert T\rvert > \lvert t\rvert)$
Frac. positive shocks	0.13	0.002	0.13	0.002	0.76	0.45
Frac. negative shocks	0.10	0.001	0.11	0.002	-5.90	0.00
Market volume traded	252.06	3.59	319.55	6.18	-9.45	0.00
Buyer's avg. market volume	2.55	0.02	2.69	29.51	-4.21	0.00
Buyer-seller ratio	7.32	0.06	7.46	0.05	-1.83	0.07
Panel B: breakup RC	*Earlier months*		*Pre-breakup months*			
	Mean	SD	Mean	SD	t-stat	$P(\lvert T\rvert > \lvert t\rvert)$
Frac. positive shocks	0.13	0.002	0.16	0.01	-4.95	0.00
Frac. negative shocks	0.12	0.002	0.08	0.004	7.92	0.00
Market volume traded	250.61	3.03	354.46	5866.81	-15.73	0.00
Buyer's avg. market volume	2.41	0.02	2.73	28.60	-9.50	0.00
Buyer-seller ratio	8.01	0.06	6.94	0.05	13.20	0.00

Note: New RC, breakup RC, form months, and pre-breakup months are defined in Section F. The buyer-seller ratio is computed by dividing the number of buyers by the number of sellers on the market on a given day. Supply shocks are defined in Section II.D. *Frac. positive/negative shocks* is the fraction of days that a given pair experiences positive/negative supply shocks out of all days when the pair trades. Market total volume traded and average buyer volume available are measured in 1,000 kg. *SD* means standard deviation.

First, buyers who form an RC experience statistically more negative supply shocks and smaller average supply per buyer in the pre-formation month and the first month of the relationship (month $m^* - 1$ and m^*; hereafter, *form months*) relative to earlier months with the buyers' presence. According to the conceptual model, the relatively limited market supply in the form months implies a relatively large ϕ_b during that period and hence a higher RC surplus to split between the buyer and seller (see equation (D8)), echoing the intuition discussed in Section IV.B.

Second, the breakup pairs experience statistically more positive supply shocks and fewer negative supply shocks in the last two months before the termination (month $m_* - 1$ and m_*; hereafter, *pre-breakup months*) relative to earlier months of their relationships. The pairs also face a larger average supply per buyer in the pre-breakup months. That is, the market supply happens to be statistically more abundant in the pre-breakup months than earlier. A relatively abundant supply implies a relatively small ϕ_b on a given day.

Our model suggests that the traders could agree upon a relatively low transaction price during positive shocks. This price, however, should not fall as much as the spot market price would to sustain the relationship. Consequently, on days with positive shocks, the buyer should pay a relatively higher RC premium. We estimate the RC premium for the pre-breakup months using equation 3, but find a statistically zero premium paid by the buyers. These buyers appear to fail (or strategically refuse) to pay a higher premium on supply-abundant days, violating the DICCs specified in Section III.

Additional Robustness Checks

We discuss additional tests on the three hypotheses and strategic defaults of RCs. Baseline results are confirmed.

Tests on Hypotheses. — We run more robustness tests on Hypothesis II. One might also be concerned about the assumption that the error in the latent variable model has a standard normal distribution (i.e., probit model) or a standard logit distribution (i.e., logit model). We employ a semi-parametric estimator developed by Klein and Spady (1993) that relaxes the parametric assumption on the error term and estimates coefficients in the response probability function consistently. The results are reported in Table G1 and confirm the baseline findings. The average partial effect of the buyer-seller ratio turns out to be 0.53 with a standard error of 0.22.

We also estimate the standard probit model using the full sample of buyer-year observations, namely, including buyers who conduct less than 20 transactions in a year. The sample is larger, containing 6,309 observations. The mean $(RT)_{i,y}$ is merely 0.05 with a standard deviation of 0.21. The mean of $B/S_{i,y}$ equals 6.94 with a standard deviation of 2.44. Table G2 reports estimated coefficients with signs and significance consistent with Table IV.B. The partial effect of the buyer-seller ratio at its mean equals 0.003 with a standard error of 0.001. The effect implies a 15% increase in the probability of forming RC if the ratio increases by one standard deviation, which also aligns with the baseline results.

Table G1—Semi-Parametric Probit Regression on Forming Relationships (Test II)

Variable	Coefficient	Std. Err.	z	P> |z|
Buyer's avg. no. sellers (S)	0.081	0.044	1.85	0.065
Buyer's avg. market volume (Mvl)	-1.487	0.684	-2.17	0.030
Buyer's avg. buyer-seller ratio (B/S)	0.534	0.218	2.45	0.014
Buyer's no. trading days	0.029	0.011	2.58	0.010
Buyer's avg. volume purchased	0.437	0.178	2.46	0.014
Buyer's avg. trading time	-0.222	0.269	-0.82	0.410
Year fixed effects	Yes			
No. observations	1,385			
Log likelihood	-506.85			

Note: Buyer's no. trading days is the number of trading days for a buyer in a given year. *Buyer's avg. purchase* is the average volume purchased for a buyer in a year. *Buyer's avg. trading time* is the average hour-minute when the first transaction of a day happens for a buyer in a year.

Table G2—Probit Regression on Forming Relationships (Test II)

Variable	Coefficient	Std. Err.	z	P> |z|
Buyer's avg. no. sellers (S)	-0.011	0.014	-0.81	0.419
Buyer's avg. market volume (Mvl)	0.205	0.150	1.36	0.173
Buyer's avg. buyer-seller ratio (B/S)	0.053	0.019	2.82	0.005
Buyer's avg. volume purchased	0.210	0.044	4.82	0.000
Buyer's avg. trading time	-0.504	0.166	-3.04	0.002
Buyer's no. trading days	0.018	0.001	22.63	0.000
Year fixed effects	Yes			
No. observations	6,309			
Log likelihood	-608.74			
Likelihood ratio χ^2	1,129.23			
$Prob > \chi^2$	0.00			

Note: Buyer's no. trading days is the number of trading days for a buyer in a given year. *Buyer's avg. purchase* is the average volume purchased for a buyer in a year. *Buyer's avg. trading time* is the average hour-minute when the first transaction of a day happens for a buyer in a year.

Concerning the sensitivity of baseline findings in Section IV.C, we vary the T/P ratio threshold and check alternative definitions of supply shocks. Table G3 reports results on Hypotheses III by varying the T/P ratio threshold. All estimates align with the baseline results in signs and magnitudes.

Recall that the baseline definition employs a two-week rolling average of daily

Table G3—Relational Adaptation under Shocks (Tests III): Varying the T/P Ratio Threshold

	(1)	(2)	(3)	(4)
Dependent variable		log(transaction price)		
RC-0.2	0.018			
	(0.011)			
RC-0.4		0.025		
		(0.011)		
RC-0.6			0.039	
			(0.012)	
RC-0.8				0.038
				(0.016)
Positive shock	-0.054	-0.054	-0.054	-0.053
	(0.005)	(0.005)	(0.005)	(0.005)
Negative shock	0.113	0.112	0.109	0.108
	(0.011)	(0.011)	(0.014)	(0.014)
RC-0.2 × Positive shock	0.010			
	(0.007)			
RC-0.4 × Positive shock		0.013		
		(0.008)		
RC-0.6 × Positive shock			0.016	
			(0.009)	
RC-0.8 × Positive shock				0.015
				(0.011)
RC × Negative shock				
RC-0.2 × Negative shock	-0.056			
	(0.026)			
RC-0.4 × Negative shock		-0.059		
		(0.028)		
RC-0.6 × Negative shock			-0.061	
			(0.018)	
RC-0.8 × Negative shock				-0.103
				(0.019)
Control variables	Yes	Yes	Yes	Yes
Seller-Month fixed effects	Yes	Yes	Yes	Yes
Hour fixed effects	Yes	Yes	Yes	Yes
No. observations	179,825	179,825	179,825	179,825
R^2	0.717	0.717	0.717	0.717

Note: Standard errors are clustered at the seller level and shown in parentheses. "RC-x" means a relationship is defined when the T/P ratio between the buyer and the seller exceeds the threshold of x, and the number of transactions is no less than 20 in the year. Shocks are defined in Section IV.C.

total volume traded on the market. Table G4 presents new estimates of Hypotheses III by varying the number of days used in calculating the rolling average — "shock-n" indicates the use of n days. For example, $n = 6$ means that total volume traded on $\frac{6}{2} = 3$ days before and three days after day t is employed in calculating the rolling average. A shock is then defined for day t if the total volume traded on t is one standard deviation below or above this average. Again, all the results agree with the baseline.

Besides, we try dropping the T/P ratio threshold in defining RC, keeping the

T threshold as prior studies do (Macchiavello and Morjaria, 2015). Relying on only one condition is less stringent than using the two conditions and hence may miscount non-RCs as RCs. On the other hand, using the more stringent baseline definition in Section IV.C potentially leaves some RCs not counted.

Column (1) in Table G5 presents the new results. The coefficient suggests an average 2.0% higher price paid by RC buyers in normal times, confirming the hypothesis that buyers under relational transactions on average pay a premium to sellers relative to spot market prices. The coefficients of supply shock variables and their interactions with the RC indicator have consistent signs and magnitudes with Table 7, too. Columns (2) to (5) show that the results are not sensitive to varying the T threshold.

Tests on Strategic Defaults. — Regarding the baseline results in Section V.C, we add a condition that further trims observations to exclude *unwilling* defaults from the sample for estimation. The condition requires that, at the time of buyer i's arrival (using the time of i's first transaction on t as proxy), seller j still has sufficient stock to fulfill i's revealed quantity demanded.

The additional condition, though, likely excludes some *strategic* defaults from the sample. In other words, the baseline condition likely fails to exclude some unwilling defaults, while this additional condition likely fails to include some strategic defaults. Neither definition is perfect, but the two samples generate similar results and jointly confirm the key determinants such as the history of defaults. The results of this robustness test are reported in Table G6.

Table G4—Relational Adaptation under Shocks (Test III): Varying the Definition of Supply Shocks

	(1)	(2)	(3)	(4)
Dependent variable		log(transaction price)		
RC	0.025	0.021	0.023	0.023
	(0.011)	(0.011)	(0.011)	(0.011)
Positive shock-6	-0.059			
	(0.005)			
Negative shock-6	0.073			
	(0.008)			
Positive shock-10		-0.038		
		(0.005)		
Negative shock-10		0.105		
		(0.009)		
Positive shock-18			-0.038	
			(0.006)	
Negative shock-18			0.109	
			(0.014)	
Positive shock-22				-0.028
				(0.007)
Negative shock-22				0.107
				(0.018)
RC × Positive shock-6	0.026			
	(0.006)			
RC × Positive shock-10		0.045		
		(0.008)		
RC × Positive shock-18			0.043	
			(0.010)	
RC × Positive shock-22				0.048
				(0.011)
RC × Negative shock-6	-0.042			
	(0.013)			
RC × Negative shock-10		-0.039		
		(0.019)		
RC × Negative shock-18			-0.066	
			(0.028)	
RC × Negative shock-22				-0.082
				(0.038)
Control variables	Yes	Yes	Yes	Yes
Seller-Month fixed effects	Yes	Yes	Yes	Yes
Hour fixed effects	Yes	Yes	Yes	Yes
No. observations	179,825	179,825	179,825	179,825
R^2	0.715	0.716	0.714	0.713

Note: Standard errors are clustered at the seller level and shown in parentheses. "Shock-n" means supply shocks are defined based on a rolling average of total volume traded for n days. RC × "Shock-n" represents interaction terms of the relationship indicator and the shock variable. Shocks are defined in Section IV.C.

Table G5—Relational Adaptation under Shocks (Test III): Dropping the T/P Ratio Threshold

	(1)	(2)	(3)	(4)	(5)
Dependent variable			log(transaction price)		
RC-14	0.020				
	(0.011)				
RC-17		0.017			
		(0.012)			
RC-20			0.018		
			(0.012)		
RC-23				0.013	
				(0.012)	
RC-26					0.011
					(0.013)
Positive shock	-0.056	-0.055	-0.054	-0.054	-0.053
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Negative shock	0.115	0.113	0.113	0.112	0.112
	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
RC-14 × Positive shock	0.019				
	(0.007)				
RC-17 × Positive shock		0.015			
		(0.007)			
RC-20 × Positive shock			0.012		
			(0.007)		
RC-23 × Positive shock				0.012	
				(0.007)	
RC-26 × Positive shock					0.012
					(0.007)
RC × Negative shock					
RC-14 × Negative shock	-0.047				
	(0.024)				
RC-17 × Negative shock		-0.050			
		(0.025)			
RC-20 × Negative shock			-0.056		
			(0.026)		
RC-23 × Negative shock				-0.056	
				(0.027)	
RC-26 × Negative shock					-0.064
					(0.027)
Control variables	Yes	Yes	Yes	Yes	Yes
Seller-Month fixed effects	Yes	Yes	Yes	Yes	Yes
Hour fixed effects	Yes	Yes	Yes	Yes	Yes
No. observations	179,825	179,825	179,825	179,825	179,825
R^2	0.717	0.717	0.717	0.716	0.716

Note: Standard errors are clustered at the seller level and shown in parentheses. "RC-n" signifies that a relationship is defined when the number of transactions between the buyer and the seller exceeds the threshold of n in the year.

Table G6—Probit Regression on Strategic Default: Alternative Definition of Strategic Default

Variable	Coefficient	Std. Err.	z	$P > \|z\|$
No. sellers	0.025	0.004	6.60	0.000
Buyer/seller ratio	0.032	0.017	1.94	0.053
Positive shock	-0.204	0.095	-2.14	0.033
Negative shock	-0.156	0.122	-1.28	0.201
Avg. purchase share last month	-1.016	0.097	-10.52	0.000
Avg. sales share last month	-0.331	0.143	-2.32	0.020
No. past defaults	0.024	0.002	10.33	0.000
Year and month fixed effects	Yes			
No. observations	9,512			
Log likelihood	-939.58			
Likelihood ratio χ^2	375.57			
$Prob > \chi^2$	0.00			

Note: The buyer-seller ratio is computed by dividing the number of buyers by the number of sellers on the market on day t. Supply shocks are defined in Section II.D.