# Relational Contracts in Well-Functioning Markets: Evidence from China's Vegetable Wholesale

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*Relational contracting (RC) is an important yet little understood governance of transactions that provides more stability than the spot market and more flexibility than vertical integration. Employing transaction data on a large vegetable wholesale market in China, we study RC alongside a well-functioning spot market. Motivated by the stylized facts found in repeated transactions — higher supply assurance for buyers, a conceptual model is set up to depict the dynamic incentive compatibility constraints of buyers and sellers who potentially form relationships. The model suggests that a price premium is paid by relational buyers in exchange for secured supply and hypothesizes how RC traders adjust the RC price as well as RC premium to sustain the relationship under supply shocks on the spot market. The empirical analysis provides supporting evidence for the hypotheses under various definitions of RC and shocks. Further, we show theoretically and empirically that RC is more likely to be formed in markets with more buyers relative to sellers or thicker markets, which the model also suggests. Taken together, we contribute novel evidence for the strategic complementarity between RC and spot markets.*

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## I. Introduction

> *Virtually every commercial transaction has within itself an element of trust, certainly any transaction conducted over a period of time. It can be plausibly argued that much of the economic backwardness in the world can be explained by the lack of mutual confidence.* K. J. Arrow

The governance of economic transactions takes three basic forms: the market, the firm (hierarchy), and the vertical coordination (long-term contract) (Williamson, 2005). Among the three forms, the market is most familiar: market prices coordinate the decentralized choices of traders and play the key role in allocating resources and governing adaptation. The firm sometimes replaces prices as the mechanisms through which resources are allocated and adaptation needs are met. In between markets and firms sits a variety of intermediate, sometimes hybrid, governance forms, namely, various vertical coordination (VC) arrangements of which formal and relational contracting are important cases.

While formal contracting has long been justified by economic theory as the most efficient form of VC, the persistence and importance of relational contracting (RC) have not been fully recognized, and RC remains the least studied governance of transactions. Studies have found that relationships — observed as repeated trade between agents — account for a large share of transactions, especially in developing countries.[1] Unlike in formal contracting, parties in relationships rely on informal agreements that are not third-party enforceable to conduct trade.

Are relationships temporary arrangements destined to disappear as markets develop, or do they represent a stable governance form? Some theoretical models predict that when outside options improve (e.g., as markets develop), a reciprocal agreement becomes less attractive to both parties, and their relationship is hard to sustain (Kranton, 1996*b*). Thus, markets and relationships are strategic substitutes — the more parties participate in market exchange, the harder it is to sustain relationships, and *vice verse*. On the other hand, markets and relationships can be strategic complements. Theoretically, for instance, a relatively liquid and well-functioning market may be needed for relationships to function properly (Macchiavello, 2022).

Empirical answers to this question are mostly based on institutionally weak settings where markets either do not exist or do not function well. In such settings, RC plays a critical role in overcoming market frictions and disciplining opportunistic behavior of traders facing high risk of delivery failure (Macchiavello and Morjaria, 2015; Cajal-Grossi, Macchiavello and Noguera, Forthcoming), high search costs in locating trading partners (Rudder, 2020), and credit constraints (McMillan and Woodruff, 1999). As these market imperfections are mitigated,

[1] A large empirical literature documents the prevalence of relationships/relational contracts across economic settings (Greif, 1993; Fisman, 2001; Fafchamps, 2003). Macchiavello (2022) gives a thorough review with a focus on developing countries. See also Gil and Zanarone (2017) for a recent review on relational contracts.

one would expect the value of RC to fall. Recently, in the context of US trucking industry, Harris and Nguyen (2022) provide new theoretical and empirical evidence that relationships substitute active spot markets, making markets *thinner* (e.g., fewer traders and less volume traded).

Could relationships sustain in a well-functioning market and even serve as a complement? If so, what are their values? We provide novel evidence of persistent relationships in a well-functioning agricultural wholesale market. The market is well-functioning in the sense that the flow of information is virtually free and complete, prices play the key role in resource allocation, the pool of traders is large, and there is little to no risk in the other party's fulfilling payment or delivery once a deal is settled. In such a market, one may naturally think that trade is anonymous and there is no room for relationships to be favorable.

Using transaction-level observations, we reveal a large number of repeated transactions among traders in this market. We rationalize the coexistence of relational trade alongside a well-functioning market by highlighting buyers' concerns about being rationed under stochastic demand and volatile supply on the market. The volatility is inherent in agricultural supply chains in developing as well as developed economies (Collier and Gunning, 1999; Asker, Collard-Wexler and De Loecker, 2014). Well-functioning markets alone are insufficient to overcome the structural supply chain inefficacy. Relationships can provide more stability than spot market exchange does. Informal contracts embedded in the relationships, as we show, are essentially informal insurance contracts to assure supply at affordable prices for buyers.

The market under scrutiny is a large wholesale market of fresh produce in China that primarily features vegetables. The total yearly trading volume is more than 3.0 million metric tons, one of the largest among all produce wholesale markets in Asia. More than 300 varieties of produce are transacted year-round. The market shares several features with agricultural wholesale markets in developing countries — there is a large number of sellers and buyers, sellers and buyers negotiate on-site, and products are highly homogeneous. Starting in 2009, transactions in the market have been recorded in a digital trading system where each trader is identified by a unique time-invariant identifier. All transactions feature on-site delivery and immediate money transfers via the digital system, leaving little to no risk in delivery or payment and making credit provisions irrelevant.

The unique transaction-trader-specific, real-time dataset has three critical advantages over prior studies. First, for each pair of traders, the history of their transactions is observed. This allows us to see if repeated trade occurs and to what extent. Second, the dataset covers a much larger number of traders and much higher-frequency transactions than most prior research. Third, our data are free from measurement errors because traders have no incentive to misreport prices or volume in the digital system as cash transfers are based on what is reported. In contrast, data obtained from field surveys and firm or industry reports likely suffer from nontrivial measurement errors.[2]

We focus on a four-year period from 2016 to 2019 and examine transactions of Chinese cabbage, a major commodity traded on this market. Three salient features of the transaction data stand out. First, prices are significantly dispersed on a single day and even for a given seller on the day. The prices that a seller quotes on a single day are dispersed, after controlling for 1) the volume of the transaction (e.g., 200 kilograms) and 2) the timing of the transaction (e.g., 9:00 a.m.). Second, repeated trade, a buyer and a seller transact with each other for a large number of times, is pervasive. Third, by exploiting the repeated transactions, we find that the volume of purchased by a buyer who conducts repeated trade tends to be more stable or less likely to be rationed relative to his/her desired amount, especially under negative market-level supply shocks.

Based on the stylized facts, we set up a conceptual framework to characterize the dynamic incentive compatibility constraints for buyers and sellers who potentially form economic relationships via repeated transactions. The central trade-off between trading on the spot market *versus* under a relational contract (RC) is having more flexibility in exploring price volatility to one's advantage *versus* having more ensured supply of products to avoid being rationed.

Our model shows that an RC in the market effectively provides informal supply insurance for buyers who pay sellers a price premium in exchange for the assurance of supply. Further, we demonstrate how the RC price and RC premium vary to sustain the RC under market-level supply shocks. We derive three key hypotheses from the model that help distinguish an RC from merely repeated trade between a buyer and a seller.

In the baseline test, we define an active RC if a pair of buyer and seller trade at least 20 times in a year, following Macchiavello and Morjaria (2015). We find that prices charged by sellers are on average 2–3% higher for RC buyers than for spot-market buyers. When market supply drops (rises) on a day and spot-market price rises (drops), the RC price increases (decreases) as well. Furthermore, when market supply drops (rises) on a day and spot-market price rises (drops), the RC price premium received by sellers decreases (increases). The baseline results are robust to several alternative definitions of an RC and shocks and support the hypotheses.

Further, we explain why, theoretically, this RC can serve as a strategic complement to the spot market. Using the number of sellers, number of buyers, and market total value traded to measure the thickness of market (Hubbard, 2001), we show empirically that RC is more likely to be formed in markets with more buyers relative to sellers given the number of sellers. That is, RC complements a *thicker* market.

Our contribution is two-fold. First, we contribute novel empirical evidence that economic relationships can be fostered in a well-functioning spot market

[2]There is extensive discussion on measurement errors in field survey data, for instance, due to inaccuracy or bias in recall information (Beegle, Carletto and Himelein, 2012).

to provide supply assurance to buyers under stochastic supply. Furthermore, markets and relationships can be strategic complements, and relationships develop with markets. Our insights help explain the wide and persistent coexistence of economic relationships with markets and firms both in developed and developing economies. Second, we are the first to use transaction data to study agricultural wholesale markets, markets that have been under-studied due to lack of data (Barrett et al., 2022). Our findings improve the understanding of rapidly evolving agricultural supply chains in low- and middle-income countries (LMICs).

### *A. Related Literature*

Exchange mechanisms form a continuum. At one extreme of the spectrum are pure arm's length spot market transactions, and at the other is vertical integration. Between these extremes are various VC arrangements (Myers, Sexton and Tomek, 2010). Close VC like formal contracting has been lacking in most LMICs in the contemporaneous period of contract development in Western countries (Barrett et al., 2022). Only since the early 2000s, the agri-food value chain transformations in LMICs have accelerated and led to a quick rise of contract farming, which helps address a number of market failures such as imperfect factor markets, missing insurance, and asymmetric information (Bellemare, Bloem and Lim, 2022).

Still, arrangements between farmers and intermediaries are extensively informal (Michler and Wu, 2020); the arrangements are often "relational" and rely on self-enforcement, which are particularly salient in LMICs where the institution for enforcing formal contracts is missing or incomplete (Bellemare, Bloem and Lim, 2022). For instance, Fafchamps (2000, 2003, 2010) has documented the importance of informal business relationships between firms in Africa and other developing economies.

The investigation on self-enforcing agreements dates back to Telser (1980) and Klein and Leffler (1981), who show formally that short-term opportunistic behavior can be disciplined by inter-temporal incentives. The next wave of theoretical advances focuses on the optimal structure of informal agreements (MacLeod and Malcomson, 1989; Baker, Gibbons and Murphy, 1994). In a model that combines contract theory and the theory of repeated games, Baker, Gibbons and Murphy (2002) characterize these "informal agreements sustained by the value of future relationships" as relational contracts. This definition provides guidance for later studies of RC (Halac, 2012; Rudder, 2020) by emphasizing that RCs are not merely repeated transactions — future rents must be recognized by both parties to deter short-term opportunistic behavior and sustain the relationship besides saving search costs for locating a trading partner.[3]

[3]There are a few models of informal relationships that do not build upon the theory of relational contract. For example, Kranton (1996*a*) shows in a structured model that agents can sustain cooperation by monotonically increasing the level of exchange within a relationship.

Prior studies have identified multiple market imperfections that imply value for RC. Poorly functioning markets increase the demand for relationships even for the exchange of simple goods because the transaction may need to be bundled with services due to market failures (Macchiavello, 2022). Two common services are the assurance of negotiated payments (McMillan and Woodruff, 1999; Antras and Foley, 2015) and the assurance of negotiated delivery (Macchiavello and Morjaria, 2015; Ghani and Reed, 2022). As market conditions evolve, one service may be replaced by another to sustain the relationship. Ghani and Reed (2022), for instance, show that delivery assurance loses its value when upstream supply becomes abundant, and relational sellers switch to providing trade credits for the buyers.

In our context, importantly, all transactions feature immediate cash transfers and real-time exchange of products, and products are homogeneous. Common market frictions like uncertainty over seller's reliability in making delivery (Macchiavello and Morjaria, 2015), lack of credit provision (Antras and Foley, 2015), and asymmetric information (Levin, 2003) are not relevant. The basis for relational contracting must lie beyond these considerations.

We share economic intuition with Ghani and Reed (2022) who highlight supply assurance as a margin of quality provided by ice retailers to fishing firms. Yet, they only infer supply assurance through the observations of late delivery. We employ a reduced-form regression and a stochastic frontier technique to more directly show that buyers with stable partners experience less frequent and less severe rationing in transactions. Focusing on a fresh fish wholesale market, Weisbuch, Kirman and Herreiner (2000) also show that the value of repeated trade for buyers is to avoid the risk of not being served and that for sellers is to predict with more accuracy the demand they face. Cajal-Grossi, Macchiavello and Noguera (Forthcoming) examine relational trade that provides supply assurance to buyers and find a price premium paid by relational buyers. We extend their insights by exploring adjustments of RC premium under supply shocks to sustain the relationship using unique, high-frequency transaction data.

Our digitally-recorded transaction data allow us to use repeated trade as a direct proxy for relational trading for a large number of trader pairs. In contrast, many previous studies rely on cross-sectional survey evidence (McMillan and Woodruff, 1999; Banerjee and Duflo, 2000) or industry and firm reports to measure relational practices (Macchiavello and Miquel-Florensa, 2018; Macchiavello and Morjaria, 2021), likely suffering from measurement errors. Antras and Foley (2015) use transaction data to study RC, but only data of a single firm.

## II. Institutional Background and Data

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 and the transaction data employed for our empirical analysis.

### *A. The Vegetable Wholesale Market*

The wholesale market of interest is located in northern China and covers an area of 200 hectares. Every year, 3-4 million metric tons of vegetables are traded on the market, amounting to annual sales of 7-10 billion RMB. As one of the largest wholesale fresh vegetable markets in China and Asia, the market 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, primary wholesale markets distinguish from *secondary* wholesale markets which trade products from an upstream, often larger-scale, primary wholesale market.

More than 300 fresh vegetables are traded on the market (e.g., broccoli, cabbage, celery, and tomatoes) over a year. Fresh vegetable products are of 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 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 of a day.

Each day, a large number of buyers and sellers come to trade face-to-face. 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 a scene of the market). For most vegetables, there are more buyers than sellers on the market. Most traders are professional traders and have been in the business for years.

About 80% of the sellers collect vegetables directly from smallholder producers located in multiple production regions, while other sellers purchase from larger-scale farms and/or farm cooperatives (Song, 2023). Within each production season, most sellers specialize in selling one vegetable like Chinese cabbage or broccoli. 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 (e.g., two truckloads of Chinese cabbage) that cannot readily be altered over a day's market. Due to high transport costs, sellers typically fill up each truck they bring to the market.[4]

Buyers can be classified into three types: 1) secondary wholesalers who sell products procured in this primary market to a downstream wholesale or retailer market that is smaller in size, 2) agents who conduct procurement for supermarkets and groceries, and 3) those procuring for restaurants and 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 his/her trucks on a given day.

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

Like many wholesale markets in LMICs, prices on this market are not posted and are negotiated by transaction. Once a seller and a buyer settle a deal, the buyer pays in cash and loads the products onto his/her truck(s) on-site, ensuring timely and full delivery and payment on this market. Prices are all free-on-board (FOB) in the sense that a buyer uses his/her own trucks to ship products and bears all the downstream shipping costs.

At first glance, such a market is highly competitive — homogeneous products, frequent transactions, large numbers of sellers and buyers, minimal entry barriers, and free and transparent information. Standard search models, like Diamond (1989), would argue that in such a market, sellers are anonymous and searched with equal probability and that there would be no memory of where favorable opportunities were found in the past.

### *B. Transaction Data*

Our empirical analysis draws on the complete set of 179,825 transactions of Chinese cabbage (CC) traded on the wholesale market, covering 2016 through 2019. CC is one of the most traded commodities on the market and is sold in bulk with no packaging. Although the shelf-life of CC varies across different downstream markets, it is considered to be perishable at the wholesale stage as overnight storage is rare. CC is also highly homogeneous, leaving little concern on inter-temporal arbitrage and quality differentiation.

Table 1—Summary statistics

| | *Chinese cabbage (No. obs.: 1440 days)* | | | |
|---|---|---|---|---|
| Variable | Mean | Standard Dev. | Min. | Max. |
| Total trading volume (kg) | 144,495.00 | 172,165.00 | 56.00 | 918,796.00 |
| Number of 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 |
| Number of buyers | 79.01 | 70.42 | 1.00 | 310.00 |
| Number of 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. Trading days are calendar days with at least one transaction of CC. *kg* means kilogram. *Buyer-seller ratio* equals the daily number of buyers divided by the daily number of sellers on the market of CC.

The dataset is extracted from a proprietary database of the market, which has not been released for academic use. The unique dataset describes each transaction

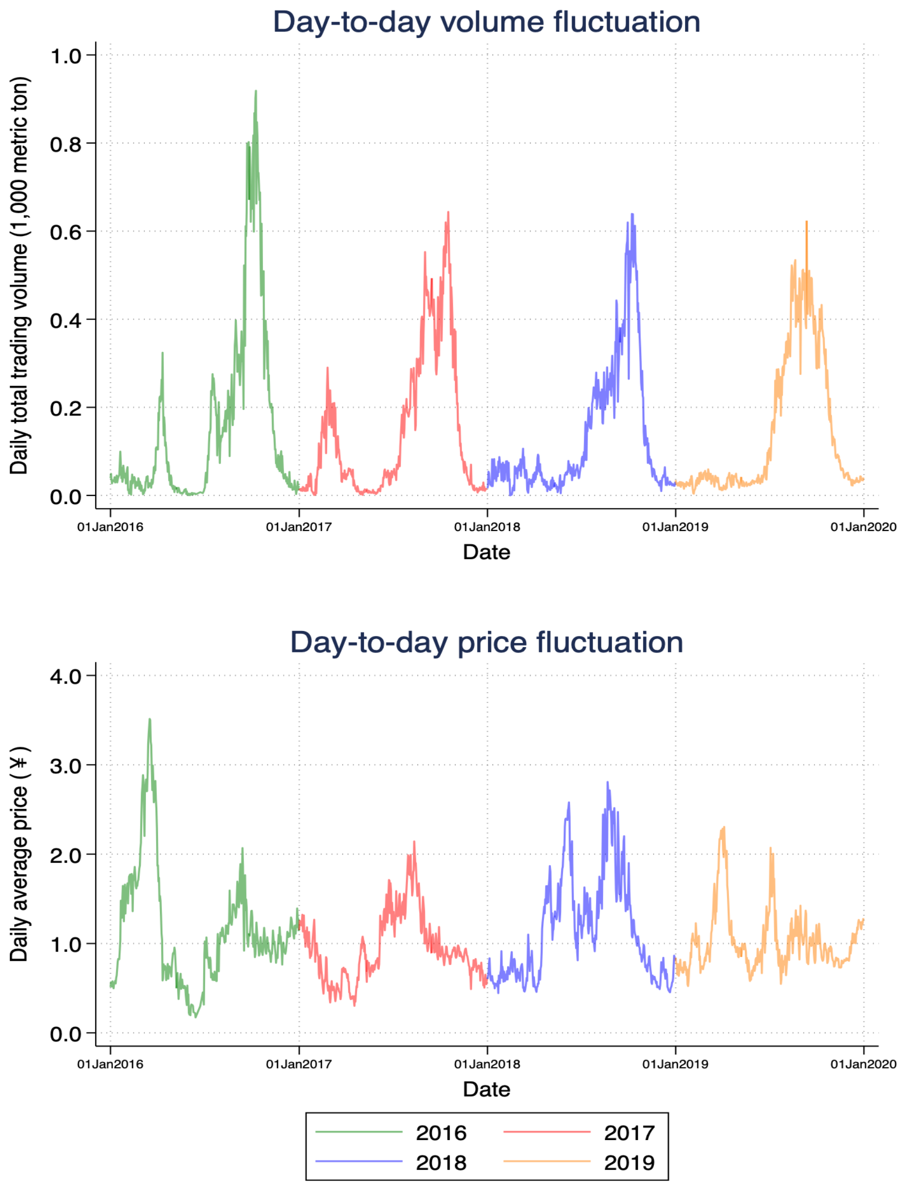


Figure 1. Day-to-day Fluctuation in Trading Volume and Price of Chinese Cabbage

*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/

by five variables: (1) date and time of the transaction (specified to second), (2) identifiers (IDs) of the buyer and seller, (3) name of the commodity, (4) quantity traded (in kilogram), and (5) price paid (in RMB/kilogram). The IDs of the buyer and the seller are time-invariant and unique 9-digit numbers. In this study, 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 the winter of 2019.

Table 1 reports summary statistics for some key variables at the trading day level. Daily market trading volume has a mean of 144,495 kilograms and a large variance due to seasonality on the CC market. On an average day, 125 transactions are made. The average transaction size is 1,045 kg, with a majority of the transactions lying between 500 to 1,600 kg. The mean weighted average price on a day is 1.12 RMB/kilogram (0.2 USD/kilogram) with a standard deviation of 0.53. The numbers of buyers and sellers vary across seasons, too, while the ratio of the two stays around 6.3. See Table A1 and Figure A2 for additional information on traders and their trading activities.

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. Market prices display strong seasonality and daily volatility, too. Market prices tend to be relatively low during peak trading seasons. Interestingly, market prices seem to be more volatile in low trading seasons than in peak seasons.

## III. Key Stylized Facts

Examining the data, two salient features of the transactions catch attention: 1) there is considerable price dispersion within individual sellers within a day that cannot be attributed to volume or timing of the transactions, and 2) there are repeated transactions between a large number of traders. We further show that repeated transactions feature supply assurance for buyers.

### *A. Price Dispersion*

In this well-functioning market, 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 50% of the price variance, and seller fixed effects account for another 32%. The market represents a kind of economic paradox in the sense that, the market seems vigorously competitive, yet prices for homogeneous goods are significantly dispersed among sellers, a feature not reflective of a competitive market.

A more striking stylized fact is the significant price dispersion is also "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. While inter-seller price dispersion could potentially be attributed to heterogeneity across sellers, why a single seller charges different prices on a given day remains intriguing. Figure 2 presents the distribution of the seller-day coefficient of variation (CV) in prices. A significant portion of the seller-day CV falls in the range of 0.10 to 0.30, indicating considerable intra-seller price dispersion.

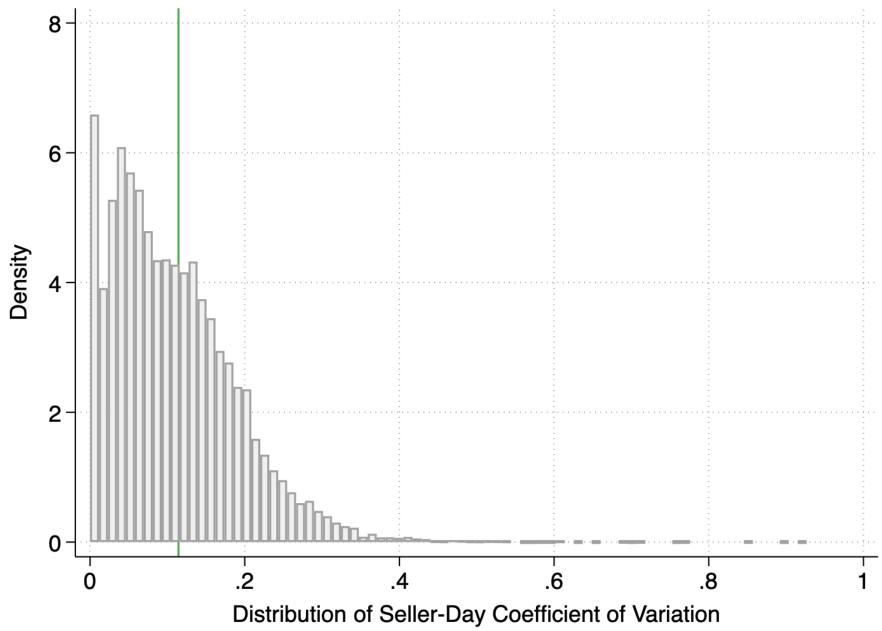


Figure 2. Distribution of Coefficient of Variation of Seller-Day Prices

*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.

### *B. Repeated Trade: Basic Features*

Browsing the transaction data, one can easily find evidence of repeated trade: a buyer and a seller transact with each other for a large number of days in a year. Repeated trade may reflect economic relationships between buyers and sellers, and economists have long suspected that relationships between agents might be important for understanding price dynamics in various markets (Wilson, 1980; Di Maggio, Kermani and Song, 2017; Hendershott et al., 2020).

We follow the literature on economic relationships to sort out observations of relatively *stable* repeated trade and examine their characteristics. Macchiavello and Morjaria (2015) suggest that pairs that trade for at least 20 transactions in a year are good candidates.[5]

Table 2, panel A reports descriptive statistics for the sample of repeated trade. In total, 541 pairs of sellers and buyers conduct repeated trade for some portion of the four-year data period. The average relationship has 34 transactions per year, ranging from 20 to 143, and trades 62,039 kilograms of CC in the year. On average, a pair of buyer and seller both come to the market for 63 days. That means, for more than 50% of days when both parties trade on the market, the pair trades with each other. In the four-year period, an average pair lasts for 223 days, and the longest lasts for 1,231 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 more than five repeated buyers, echoing the large buyer-seller ratio in Table 1.

Table 2—Summary Statistics: Repeated Trade

| Variable | No. Obs. | Mean | SD | Min. | Max |
|---|---|---|---|---|---|
| *Panel A: repeated trade characteristics* | | | | | |
| No. trading days/year | 541 | 33.98 | 16.22 | 20 | 143 |
| Trading Volume/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: No. 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: SD* means standard deviation, *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.

### *C. Repeated Trade: Supply Assurance*

Field surveys indicate that not being able to procure the amount desired is a major concern for buyers in this market (Song, 2023). 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, Forthcoming). To see if repeated trade provides supply assurance, we employ the technique

[5]The cutoff in Macchiavello and Morjaria (2015) is 20 times in 20 weeks. The peak season of CC usually lasts for 4-5 months, roughly 20 weeks, too.

in Macchiavello and Morjaria (2015) and Ghani and Reed (2022), 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:

$$\hat{R}_{i,t} = \frac{q_{i,t}}{\bar{q}_{i,t}}. \tag{1}$$

A simple regression follows:

$$\begin{aligned}\hat{R}_{i,t} =& \alpha + \beta_1 1(RT)_{i,y(t)} + \beta_2 1(RT)_{i,y(t)} \times 1(NS)_t + \beta_3 1(NS)_t \\ &+ X_{i,t}\gamma + \tau_{y(t)} + \tau_{m(t)} + \mu_i + \epsilon_{i,t},\end{aligned} \tag{2}$$

where and $1(RT)_{i,y(t)}$ 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 supply shock on day $t$. A negative supply shock means that the day has a total volume traded that is one standard deviation below the two-week rolling average, computed as the simple averaged daily market volumes for seven days before and seven days after $t$. In our context, the total volume traded on the market is predominantly driven by the supply because any volume delivered to the market is typically sold out within a day. The causes of supply shocks are mixed, including weather shocks in production regions, high-way lockdowns, and non-presence of big sellers. 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 two-week 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, $\mu_i$, to control for time-invariant characteristics of buyers.

Columns (1)-(4) in Table A2 report the results. For columns (1) and (2), the baseline definition using a two-week rolling average is employed. For columns (3) and (4), we change the control period to one week for $1(RT)_{i,y(t)}$ and $1(NS)_t$. We find that the effect of repeated trade on normal-time supply reliability is positive, suggesting that buyers who conduct repeated trade enjoy higher supply assurance than those who do not. Further, the reliability in supply is reduced by negative supply shocks on average, and buyers who conduct repeated trade achieve higher supply reliability than buyers without repeated partners under the shocks. The results are not sensitive to the length of the rolling window.

To confirm the findings, Appendix C employs a more sophisticated way to estimate the quantity rationed at the buyer level. The estimation is based on a stochastic frontier technique developed by Kumbhakar, Parmeter and Tsionas

(2013). It assumes that each buyer $i$ has a function of desired volume to purchase that is determined by the efficiency frontier and allows the buyer's actual purchase to fall inside the frontier, namely, being rationed. On day $t$, the estimation predicts a probability of being rationed, $\rho_{it}$, and a magnitude rationed relative to the desired quantity, $m_{it}$, for buyer $i$. If $\rho_{it}$ is smaller than 5%, we claim that $i$ is not rationed on day $t$. Otherwise, we say that $i$ has an inefficiency score of $m_{it}$ on day $t$.

Restricting the estimation to the sub-sample of buyers who visit the market for relatively large numbers of days ($T > 200$), we compare the likelihood and magnitude of being rationed between the group of buyers who conduct repeated trade and the group of buyers who do not. As Table C1 reports, the average likelihood of being rationed is 18.1% lower for the former than for the latter. When rationed, buyers who conduct repeated trade are rationed to a smaller extent; they get on average 11.9% more of the desired amounts than their nomad counterparts.

Summary. — Macchiavello (2022) points out that the emphasis on the role of the value of future relationships in deterring opportunism distinguishes merely repeated trade from relational trade. Repeated-trade pairs discussed above have economic relationships if they develop informal agreements to discipline their behavior and if their interactions are sustained by the future value of continued interactions.

## IV. Conceptual Framework

The section sets up a conceptual model to illustrate the basic economic forces that support an RC between a seller and a buyer who conduct repeated transactions. Unlike most RC studies where relationships are modeled as the only available form of transactions in a given market or a form separate from other forms, we consider RC alongside an active spot market and traders costly switch between or combine the two forms of transactions.[6]

Though we characterize the model based on stylized facts observed in a vegetable wholesale market in China, markets in other settings may share key features, including pre-committed and stochastic demand and supply, and can also be understood via this model. The model produces testable hypotheses that such an RC should demonstrate, helping distinguish economic relationships sustained by the future value of continued interactions from merely repeated trade.

[6]For example, Macchiavello and Morjaria (2015) take the existence of direct relationships as given and do not consider the coexistence of RC and a spot market. By separation between forms, we mean that, for instance, a trader trades with an RC partner or on the spot market. Such two-tier market structures have been documented in many contexts, like labor (Shapiro and Stiglitz, 1984) and perishable agricultural commodities (Macchiavello and Morjaria, 2015). Fafchamps (2010) provides an overview of two-tier markets in LMICs. In those studies, a strict barrier between relational and spot markets is assumed.

Every business day, a seller comes to the market with a pre-committed and stochastic supply that cannot be readily altered over a day's market. A seller may sell to 1) nomad buyers on the spot market who randomly show up with heterogeneous demands and have no memory of past transactions and/or 2) relational buyers on the market of repeated trade who show up with quantities and prices specified by the RC, though may default. Similarly, a buyer may purchase from nomad sellers on the spot market and/or relational sellers given his/her demand function. There is no separation between relational and spot markets.

Our market of interest shares two key features with markets studied by a large strand of theoretical and empirical research on dynamic pricing: pre-committed supply of sellers and random demand of buyers. This literature concludes that, in such markets, even fully flexible pricing would leave some buyers unable to fulfill desired quantities, echoing evidence of supply unreliability in Section III.C.[7] In Appendix D, we illustrate that, with a similar rationale, a positive likelihood of being rationed also applies to buyers in our context.

Dynamic incentive compatibility constraints (DICCs) underpin our model of RC. DICCs essentially state that the trading parties shall not breach the RC so long as the future relationship-specific gains are sufficient to prevent opportunistic behavior (Macchiavello, 2022).

For a trader, the DICC is expressed as:

$$(U_{t+1} - U^0_{t+1}) \geq \pi_t \tag{3}$$

where $U_{t+1}$ denotes the present value of the payoffs from continuing RC from period $t+1$ on, $U^0_{t+1}$ is the present value of the outside option from period $t+1$ on, the $\pi_t$ is the present value of defaulting the RC in period $t$. We assume that one failure of RC leads to the termination of the relationship with probability one, which is the worst punishment and mathematically consistent with less severe punishment (Abreu, 1988; Macchiavello, 2022). We relax this assumption in Section V.E.

### *A. Setup*

Supply and demand are highly volatile in the market as Section II.B shows. Determined by market supply and demand in period $t$, the spot-market price is also volatile and denoted by $p_t$. 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 $p_t$. Spot-market traders have no memory of the history of transactions with each other.

In each period, the buyer purchases $q_t$ units of a vegetable from the seller

[7]Supply insecurity is common in LMICs. For example, Cajal-Grossi, Macchiavello and Noguera (Forthcoming) argue that imperfect contract enforcement is the reason for supply insecurity and discuss the role of relational trade in the context of garment exports.

which the buyer sells to a downstream market 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 the wholesale market is highlighted.

The buyer and the seller may form an RC and potentially interact an indefinite number of periods $t = 1, 2, ...$ under a common time discount factor, $0 < \delta < 1$. The RC can be denoted by $C_t = \{q_t, p_t^{RC}\}_{t=1}^{\infty}$ as set by the pair of traders in period $t$ for current and future transactions based on expectation. This informal contract can be updated each period and specifies quantities to be delivered in a period and a price to be paid upon delivery.

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). In reality, the delivery is typically arranged by a phone call or text message between $b$ and $s$ shortly before the transaction takes place. 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. The right-hand side (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 is

$$(p^D - p_t)(1 - \phi^b) - (p^D - p_t^{RC}). \tag{4}$$

The net return from default for the seller is

$$-p_t^{RC} + p_t. \tag{5}$$

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

The left-hand side (LHS) of DICC captures the expected difference between continuing the RC and staying on the spot market from period $t+1$ and on. The latter is easy to obtain for the buyer

$$b : U_{t+1}^{b0} = (p^D - \overline{p})(1 - \phi^b)\frac{\delta}{1 - \delta}, \tag{6}$$

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

$$s : U_{t+1}^{s0} = (\overline{p} - p^U)\frac{\delta}{1 - \delta}. \tag{7}$$

We define a variable $\mu_t$ as the expected probability that RC is executed in any period after $t$, which is updated after each period and an increasing function of

RC age based on the Bayes' Theorem (see Appendix E for details). Without additional information about the future, we assume that the buyer and seller expect $p_t^{RC}$ for all post-$t$ periods and expect all future market prices at $\bar{p}$, the mean price given the spot price distribution.

The total discounted payoff under 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 8.

$$
\begin{aligned}
U_{t+1}^b &= \sum_{\tau=1}^{\infty}(p^D - p_t^{RC})\mu_t\delta^\tau \\
&+ \sum_{\tau=1}^{\infty}\mu_t^{\tau-1}(1-\mu_t)\delta^\tau[(p^D-\overline{p})(1-\phi^b) + \sum_{T=1}^{\infty}(p^D-\overline{p})(1-\phi^b)\delta^T] \\
&= (p^D - p_t^{RC})\frac{\mu_t\delta}{1-\mu_t\delta} + (p^D-\overline{p})(1-\phi^b)\frac{\delta}{1-\delta}\frac{1-\mu_t}{1-\mu_t\delta}.
\end{aligned} \tag{8}
$$

We hence express the LHS for buyer $b$

$$
\begin{aligned}
\Delta U_{t+1}^b &= (p^D - p_t^{RC})\frac{\mu_t\delta}{1-\mu_t\delta} - (p^D-\overline{p})(1-\phi^b)\frac{\delta}{1-\delta}\frac{\mu_t(1-\delta)}{1-\mu_t\delta} \\
&= [-p_t^{RC} + p^D\phi^b + \overline{p}(1-\phi^b)]\frac{\mu_t\delta}{1-\mu_t\delta}.
\end{aligned} \tag{9}
$$

Similarly, the LHS for the seller $s$ is

$$
\Delta U_{t+1}^s = (p_t^{RC} - \overline{p})\frac{\mu_t\delta}{1-\mu_t\delta}. \tag{10}
$$

It is intuitive to see that both $\Delta U_{t+1}^b$ and $\Delta U_{t+1}^s$ increase in $\mu_t$ and $\delta$. That is, the lower probability of RC default and the more traders value the future, the more valuable an RC is. The sum of these two terms equals the net aggregate surplus of continuing RC in period $t$ is

$$
\Delta S_{t+1} = (p^D - \overline{p})\phi^b\frac{\mu_t\delta}{1-\mu_t\delta}.^8 \tag{11}
$$

[8] $\Delta S_{t+1}^s$ is positive as long as $p^D > \overline{p}$. Given that the sum of RHS terms is $-(p^D - p_t)\phi^b$, this seems to suggest that 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 fixed cost for establishing an RC (Cajal-Grossi, Macchiavello and Noguera, Forthcoming), 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.

### B. Testable Hypotheses

An RC has the same design as a formal contract, but lacks legal enforcement, exposing the two parties to opportunistic breach. For the seller, the buyer could switch to a spot-market seller to capture low prices. For the buyer, likewise, the seller may default to capture high prices on the spot market. To sustain the RC, $\Delta S_{t+1}$ needs to be divided by $b$ and $s$ to deter the opportunistic behavior of both parties.

The division of potential RC surplus is realized by a price premium/discount of RC transactions relative to spot-market transactions, $p_t^{RC} - p_t$, and is 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.

Thus, the DICC for the buyer is binding, namely, expression 9 equalizes expression 4. Mathematically, the binding buyer DICC implies

$$\Delta U_{t+1}^b = (p^D - p_t)(1 - \phi^b) - (p^D - p_t^{RC}). \tag{12}$$

This implies

$$p_t^{RC} = p^D \phi^b + \bar{p}(1 - \phi^b) + (p_t - \bar{p})(1 - \phi^b)(1 - \mu_t \delta). \tag{13}$$

The seller obtains the rest of the RC surplus, leaving expression 10 no less than expression 5. The mathematical meaning is

$$(p_t^{RC} - \overline{p})\frac{\mu_t \delta}{1 - \mu_t \delta} > -p_t^{RC} + p_t. \tag{14}$$

Hypothesis I. — Our conceptual model has characterized a potential relationship between buyer and seller on the market as an informal insurance contract that provides buyers with supply assurance. Intuitively, one would expect the buyer to pay an *insurance premium* to the seller.

Mathematically, equation 14 suggests that

$$p_t^{RC} > \bar{p} + (p_t - \bar{p})(1 - \mu_t \delta). \tag{15}$$

On average, the term $(p_t - \bar{p})(1 - \mu_t \delta)$ vanishes, implying that the RC price must be larger than $\bar{p}$. We hence derive the first hypothesis

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

Hypothesis II. — As demand and supply fluctuate, spot market $p_t$ varies and deviates from $\bar{p}$. Buyer and seller can adjust $p_t^{RC}$ to sustain the RC under such shocks so that the surplus of continuing RC is retained.

For instance, if the market price rises (i.e, $p_t > \bar{p}$ under a negative supply shock), the RHS of inequality 15 rises due to a positive $(p_t - \bar{p})(1 - \mu_t\delta)$ and may incentivize the seller to default. The two parties may hence agree upon a higher, one-time $p_t^{RC}$ to satisfy the new inequality 15 as well as equation 13. Similarly, if the market price drops (i.e., a positive supply shock), the two parties may agree upon a lower $p_t^{RC}$ to satisfy the new inequality 15.

- **Hypothesis II**: *RC price varies with spot-market prices; it rises if the market price increases (a negative supply shock) and falls as the market price drops (a positive supply shock).*

Hypothesis III. — Recall that the DICC of the buyer is binding. Subtracting both sides by $p_t$, we obtain the period-specific price premium of the RC

$$p_t^{RC} - p_t = p^D\phi^b + \bar{p}(1-\phi^b)\mu_t\delta - p_t(\phi^b + \mu_t\delta - \phi^b\mu_t\delta), \tag{16}$$

where $\phi^b + \mu_t\delta - \phi^b\mu_t\delta > 0$ because $\phi^b$, $\mu_t$, and $\delta$ are all positive and smaller than 1.0.

Thus, the RC premium in period $t$ varies with $p_t$. The premium decreases as $p_t$ rises and increases if $p_t$ falls. Intuitively, the one-time premium shrinks as $p_t$ rises because the RC price is partly determined by the long-term expected returns of repeated transactions. A one-time price deviation hence only partially passes through into $p_t^{RC}$, resulting in a temporary fall in $p_t^{RC} - p_t$.

- **Hypothesis III**: *RC premium is suppressed if the market price increases (a negative supply shock) and is enlarged as the market price drops (a positive supply shock).*

## V. Empirical Results

This section presents empirical evidence for the hypotheses and performs a set of tests to demonstrate the robustness of baseline results. Further, we argue theoretically that market *thickness* affects the formation of RC and provides empirical support to the strategic complementarity between RC and spot transactions. In addition to testing the hypotheses, we examine determinants of strategic default in relational contracting. Evidence suggests that low strength of the relationship tends to result in strategic default, which is again rationalized by our model.

### *A. RC Premium*

To test Hypothesis I, we need to explain the "within" seller 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, $R_{ij,t}$ equals one if the transaction is conducted by a relational pair of seller and buyer on day $t$. As in Section III.C, we let $R_{ij,t} = 1$ if the number of transactions by a given pair in a year passes a threshold. We set the baseline threshold at 20 and try various cutoffs from 14 to 26 as robustness checks.

Vector $Z_{ij,t}$ accounts for the volume of the transaction and relative importance of the transaction to the buyer and to the seller, namely, the share of this transaction in buyer $i$'s total sales on day $t$ and share of this transaction in seller $j$'s total purchase on day $t$. Vector $B_{i,y(t)}$ captures buyer characteristics in the year that potentially affect the formation of RC and prices. The characteristics include buyer $i$'s average purchase volume per transaction, average time of transaction, and total number of days trading on the market.

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, which is constrained by the seller's truck capacity, and quality of supply for the seller on the day. Hour fixed effects (e.g., 9-10 a.m.), $\tau_{h(t)}$, absorb market-level within-day price volatility. Term $\epsilon_{ij,t}$ contains errors that are clustered at the seller level.

$$\ln P_{ij,t} = \alpha + \beta R_{ij,t} + Z_{ij,t}\gamma + B_{i,y(t)}\eta + \theta_{j,t} + \tau_{h(t)} + \epsilon_{ij,t} \tag{17}$$

Column (1) in Table 3 presents the result for this test. The coefficient suggests an average 2.3% higher price paid by RC buyers, supporting the hypothesis that buyers under relational transactions on average pay a premium to sellers relative to spot market prices.

Figure 3 displays the coefficient of the relationship indicator under various definitions of RC. A cutoff $n$ means that a relationship is assumed to exist between a buyer-seller pair if the two have transacted for at least $n$ times in a year. The point estimates are all positive and significant and suggest that a 2% premium is paid by relational buyers. Note that as we increase $n$, the significance falls slightly as $n$ becomes larger than 20. This is so likely because we set $R_{ij,t} = 0$ for some actual relationships by raising the bar too high, suggesting that it makes good sense to put the baseline at $n = 20$.

### *B. RC Price and RC Premium under Shocks*

To test Hypotheses II and III, we interact the relationship dummy with the supply shock dummies to equation 17. The main identifying variation that we leverage comes from large and stochastic jumps in market supply relative to the smooth seasonal trend and sequential swings in the sport-market price. The supply volatility could be caused by weather shocks on farms, road conditions, and other exogenous factors that are unlikely anticipated by traders on the wholesale market and hence not incorporated in the terms of RC (Macchiavello, 2022). Employing large supply and corresponding price swings also mitigates noise in

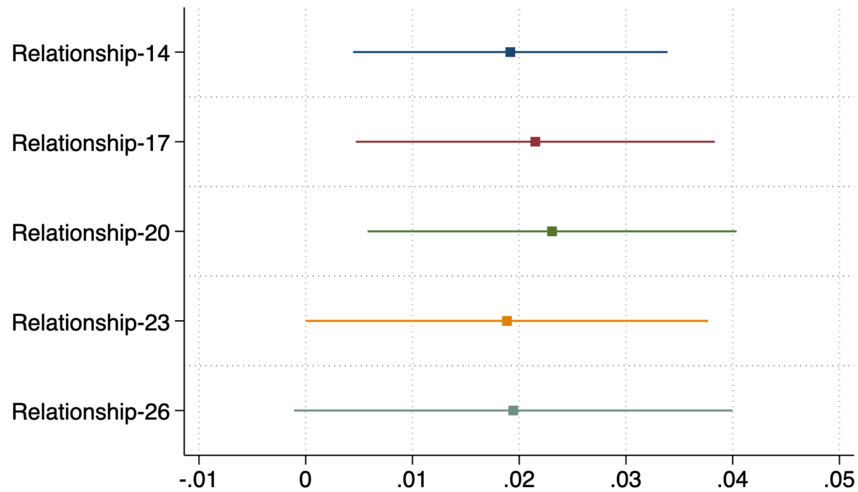


FIGURE 3. ESTIMATED PRICE PREMIUM PAID BY RELATIONAL BUYERS

*Note:* A relationship is active if a pair of buyer and seller trade at least $n$ times in a year where $n$ varies on the vertical axis (e.g., 20 times). The x-axis is the coefficient of the relationship dummy. The point of each bar is the point estimate, while the bar covers the corresponding 90% confidence interval.

the RC price and RC premium that could be driven by small volatility in factors like $\delta$, $\mu$, or $\phi^b$ in equation 13 and equation 16.

As is in Section III.C, days with supply shocks are identified as days when the market total volume traded increases or decreases drastically from the rolling average. Specifically, days with volume sales one standard deviation below the two-week rolling average are denoted as days with negative supply shocks, while days with volume sales standard deviation above the rolling average experience positive supply shocks. The positive (negative) shock indicator is denoted $1(PS)_t$ ($1(NS)_t$).

The econometric model is specified as

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

where $Z_{ij,t}$, $B_{i,y(t)}$, and $\tau_{h(t)}$ are specified in equation 17. 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 18. The error term, $\varepsilon_{ij,t}$, is again clustered at the seller level.

Estimation results of equation 18 are reported in Column (2) of Table 3. When there is a positive (negative) supply shock, the average spot market price decreases

Table 3—Relational Premium and Relational Price (Tests I, II, & III)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent variable: | Transaction price | Transaction price | Transaction price | Transaction price |
| RC-20 | 0.023** | 0.017 | | |
| | (0.010) | (0.012) | | |
| RC-14 | | | 0.020* | |
| | | | (0.011) | |
| RC-26 | | | | 0.011 |
| | | | | (0.013) |
| Positive Shock | | -0.053*** | -0.056*** | -0.053*** |
| | | (0.005) | (0.006) | (0.005) |
| Negative Shock | | 0.110*** | 0.115*** | 0.112*** |
| | | (0.011) | (0.010) | (0.011) |
| RC-20 × Positive Shock | | 0.015** | | |
| | | (0.007) | | |
| RC-14 × Positive Shock | | | 0.019** | |
| | | | (0.007) | |
| RC-26 × Positive Shock | | | | 0.012* |
| | | | | (0.007) |
| RC-20 × Negative Shock | | -0.056** | | |
| | | (0.026) | | |
| RC-14 × Negative Shock | | | -0.047** | |
| | | | (0.024) | |
| RC-26 × Negative Shock | | | | -0.064** |
| | | | | (0.027) |
| Control variables | Yes | Yes | Yes | Yes |
| Seller-Day FE | Yes | No | No | No |
| Seller-Month FE | No | Yes | Yes | Yes |
| Hour FE | Yes | Yes | Yes | Yes |
| No. observations | 77,249 | 179,825 | 179,825 | 179,825 |
| $R^2$ | 0.852 | 0.717 | 0.717 | 0.716 |

*Note:* * $p$-value< 10%, ** $p$-value< 5%, *** $p$-value< 1%. 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. Transaction prices are in log forms.

(increases) by $\hat{\beta}_2 = 0.053$ ($\hat{\beta}_3 = 0.110$) or 5.3% (11%). For Hypothesis II, we check changes in RC prices under shocks by reading $\hat{\beta}_2 + \hat{\beta}_4$ and $\hat{\beta}_3 + \hat{\beta}_5$. As the spot market 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 3.8% (5.4%).

The results indicate that $p^{RC}$ tends to be *stickier* than the market price; the change of $p^{RC}$ is smaller than that in market price. We show with an additional test in Appendix F that the volatility of price in repeated transactions is indeed smaller than the spot market price. In this sense, RC also serves as a *cushion* that buffers large price swings for relational traders.

For Hypothesis III, we check changes in the RC premium under shocks by reading $\hat{\beta}_1 + \hat{\beta}_4$ and $\hat{\beta}_1 + \hat{\beta}_5$ in Table 3. When there is a positive supply shock, the RC premium increases to 3.2% and is significant. When there is a negative supply shock, the RC premium decreases to -3.9% and is statistically zero. Compared with the premium of 2.3% in normal times, the RC premium is suppressed under a negative supply shock and enlarged under a positive supply shock, varying in the opposite direction as the market price.

Similar to Figure 3, we check if the test results for Hypotheses II and III are sensitive to the definition of RC by varying the cutoff in defining the RC indicator. Columns (3) and (4) in Table 3 report results of robustness tests by setting the cutoff *number of yearly transactions* to 14 and 26, respectively, instead of 20. The results align in magnitudes and signs with estimates reported in column (2).

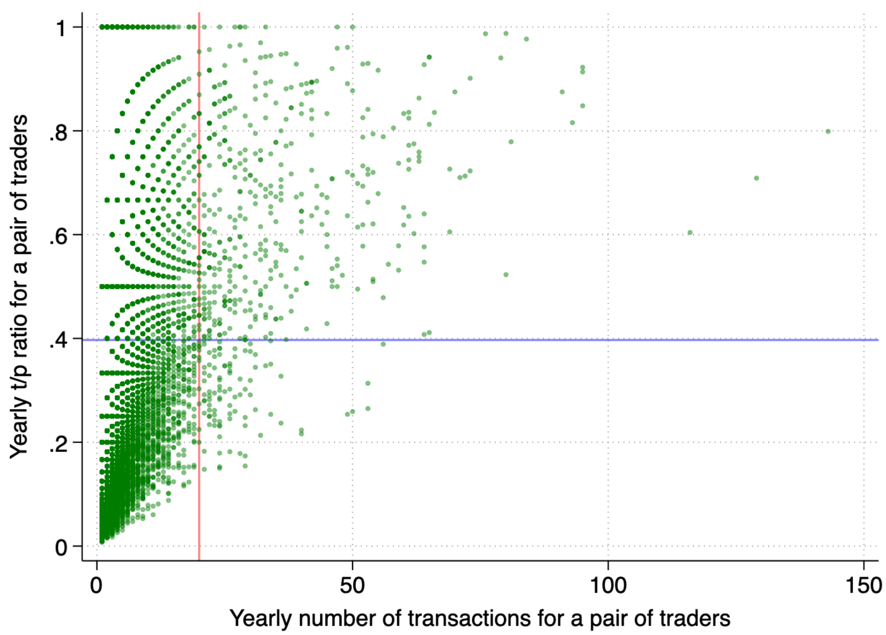


Figure 4. The "Trade-Present" Ratio versus Number of Trade Days

*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 red line represents the cutoff (*number of transactions by the pair* = 20) for the baseline definition of RC. The blue line indicates the mean of the $t/p$ ratio, which equals 0.40.

### C. Robustness Checks

The robustness of baseline results is examined in this subsection. First, we consider alternative definitions of an RC. 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 over *the number of days when both of them are present on the market* in a given year, reflective of the exclusivity of the relationship.

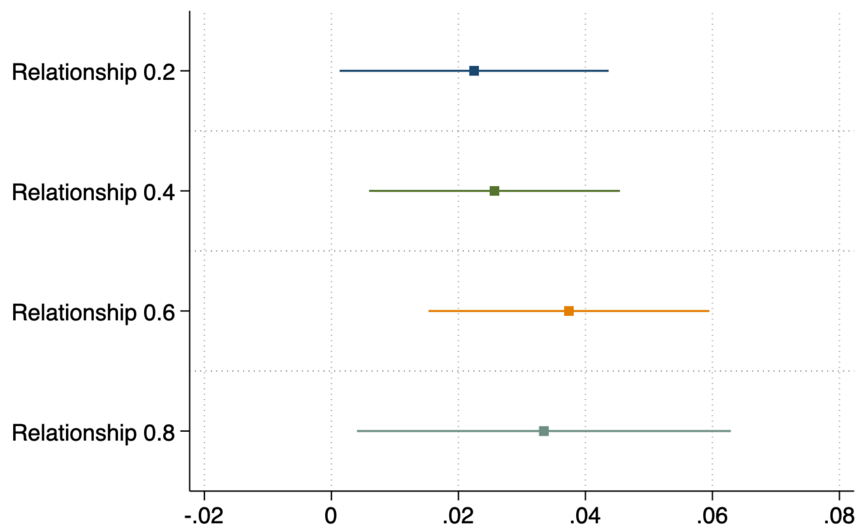


Figure 5. Price Premium in Relational Transactions: Robustness Checks

*Note:* A relationship is active if a pair of buyer and seller trade at least 20 times in a year and have a $t/p$ ratio larger than $x$ where $x$ varies on the vertical axis (e.g., 0.2). The x-axis is the coefficient of the relationship indicator in equation 17. The point of each bar is the point estimate, while the bar covers the corresponding 95% confidence interval.

Figure 4 plots the $t/p$ ratio over the number of trade days for each pair of buyer and seller. Each dot represents a buyer-seller pair. Dots to the right of the red line are pairs between which a relationship is active for at least one of the four years according to our baseline definition of RC. There is a positive correlation between the $t/p$ ratio and the yearly number of transactions for a pair. The more transactions a pair conducts in a year and the more they trade with each other whenever both come to the market, the stronger their relationship likely is.

We check if excluding buyer-seller pairs with relatively low fidelity, namely, relatively small $t/p$ ratios would affect the baseline estimates. Specifically, we have an active economic relationship between a buyer-seller pair if the two have transacted at least 20 times in a year and have a $t/p$ ratio larger than a cutoff, $x$, where $x$ equals 0.2, 0.4, 0.6, and 0.8, respectively.

Figure 5 shows the coefficients of various relationship indicators in equation 17. The point estimates are all positive and significant at the 95% confidence level, not sensitive to the $t/p$ ratio cutoff, and suggest that a 2–4% price premium is paid by relational buyers on average.

Table 4—Relational Premium and Relational Price under Shocks (Tests II & III): Varying the $t/p$ Ratio Cutoff

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent variable: | Transaction price | Transaction price | Transaction price | Transaction price |
| RC-0.2 | 0.018 | | | |
| | (0.011) | | | |
| RC-0.4 | | 0.025** | | |
| | | (0.011) | | |
| RC-0.6 | | | 0.038*** | |
| | | | (0.012) | |
| RC-0.8 | | | | 0.037** |
| | | | | (0.016) |
| Positive Shock | -0.053*** | -0.053*** | -0.052*** | -0.051*** |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| Negative Shock | 0.110*** | 0.109*** | 0.106*** | 0.105*** |
| | (0.011) | (0.011) | (0.014) | (0.014) |
| RC-0.2 × Positive Shock | 0.014** | | | |
| | (0.007) | | | |
| RC-0.4 × Positive Shock | | 0.017** | | |
| | | (0.007) | | |
| RC-0.6 × Positive Shock | | | 0.019** | |
| | | | (0.009) | |
| RC-0.8 × Positive Shock | | | | 0.021** |
| | | | | (0.011) |
| RC-0.2 × Negative Shock | -0.056** | | | |
| | (0.027) | | | |
| RC-0.4 × Negative Shock | | -0.058** | | |
| | | (0.028) | | |
| RC-0.6 × Negative Shock | | | -0.059*** | |
| | | | (0.019) | |
| RC-0.8 × Negative Shock | | | | -0.101*** |
| | | | | (0.020) |
| 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 |
| $R^2$ | 0.716 | 0.717 | 0.717 | 0.716 |

*Note:* * $p$-value< 10%, ** $p$-value< 5%, *** $p$-value< 1%. "RC-$x$" means a relationship is defined when the $t/p$ ratio between the buyer and the seller exceeds the cutoff of $x$. Standard errors are clustered at the seller level and shown in parentheses.

Table 5—Relational Premium and Relational Price under Shocks (Tests II & III): Varying the Definition of Supply Shocks

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent variable: | Transaction price | Transaction price | Transaction price | Transaction price |
| Relationship | 0.015 | 0.010 | 0.013 | 0.012 |
| | (0.012) | (0.011) | (0.012) | (0.011) |
| Positive Shock-6 | -0.061*** | | | |
| | (0.005) | | | |
| Negative Shock-6 | 0.074*** | | | |
| | (0.008) | | | |
| Positive Shock-10 | | -0.041*** | | |
| | | (0.005) | | |
| Negative Shock-10 | | 0.105*** | | |
| | | (0.009) | | |
| Positive Shock-18 | | | -0.040*** | |
| | | | (0.006) | |
| Negative Shock-18 | | | 0.111*** | |
| | | | (0.013) | |
| Positive Shock-22 | | | | -0.031*** |
| | | | | (0.007) |
| Negative Shock-22 | | | | 0.110*** |
| | | | | (0.017) |
| RC × Positive Shock-6 | 0.029*** | | | |
| | (0.006) | | | |
| RC × Positive Shock-10 | | 0.051*** | | |
| | | (0.007) | | |
| RC × Positive Shock-18 | | | 0.048*** | |
| | | | (0.009) | |
| RC × Positive Shock-22 | | | | 0.057*** |
| | | | | (0.010) |
| RC × Negative Shock-6 | -0.038*** | | | |
| | (0.013) | | | |
| RC × Negative Shock-10 | | -0.030 | | |
| | | (0.020) | | |
| RC × Negative Shock-18 | | | -0.060** | |
| | | | (0.028) | |
| RC × Negative Shock-22 | | | | -0.074** |
| | | | | (0.036) |
| 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:* * $p$-value< 10%, ** $p$-value< 5%, *** $p$-value< 1%. "Shock-$n$" means supply shocks are defined based on a rolling average of total trading volumes for $n$ days. RC × "Shock-$n$" represents interaction terms of the relationship indicator and the shock variable. Standard errors are clustered at the seller level and shown in parentheses.

Next, we check if the results of tests on Hypothesis II and III are sensitive to considering the $t/p$ ratio. Table 4 reports results by varying the $t/p$ *ratio* cutoff in the definition of RC. All estimates align with the baseline results in signs and magnitudes. As we strengthen the definition of an RC by raising the cutoff $t/p$ *ratio*, the point estimate of RC premium tends to rise slightly.

Further, we check alternative definitions of supply shocks. Recall that the baseline definition employs a two-week rolling average of daily total volume traded on the market. Table 5 presents the results of Hypothesis tests II and III by varying the number of days used in calculating the rolling average — "shock-$n$" means $n$ days are used. For example, $n = 6$ means total volume traded on $\frac{6}{2} = 3$ days before day $t$ and on three days after day $t$ are employed in calculating the rolling average. A shock is then defined for day $t$ if the total trading volume on $t$ is one standard deviation below or above this average. Again, all the results agree with the baseline results.

To conclude, we have provided solid evidence that the repeated trade on the market reflects underlying relational contracts between the buyers and sellers because a price premium is paid by buyers as theory predicts and the contractual terms like RC price and RC premium are adjusted under market-level supply shocks in ways that would, in theory, help sustain the relationships.

### *D. Complementarity between Relational Contracts and Spot Markets*

So far, we have provided solid evidence that the repeated trade observed between a large number of buyers and sellers on the wholesale market is based upon economic relationships between the traders. Alongside an active spot market, the relationship effectively serves as an informal supply insurance for buyers who face risks of being rationed. In exchange, buyers pay a price premium to sellers.

The risk of being rationed is determined by the interactions among all buyers and sellers on the market and the day. For a buyer, his/her constrained demand and the stochastic residual supply jointly create the risk. As Appendix D illustrates, the smaller the residual supply is, the higher the quantity rationed for a buyer with a downstream obligation, or larger $\phi^b$ is in Section IV.

Equation 11 suggests that the surplus of forming an RC increases in $\phi^b$. As long as the downstream price is higher than the expected wholesale price and the fixed cost of forming RC is sufficiently small (e.g., cost of initial matching and negotiation for a pair of traders), the net quasi-rent from RC is positive. The larger $\phi^b$, the more likely that the net quasi-rent is positive, everything else the same. The positive quasi-rents should be captured by forming RC to achieve efficiency in the market.

Empirically, when would the residual supply be relatively small and $\phi^b$ be large? Given the total supply on the market, the larger 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-market buyers, is considerably larger in peak seasons compared with lean seasons. Peak seasons also see more sellers and larger total volumes traded on the market. Larger numbers of traders and large trading volumes mean *thicker* markets (Hubbard, 2001). Therefore, a thicker spot market tends to imply a smaller residual supply, a higher risk of being rationed for a given buyer, and a higher value of forming RC. That market thickness induces RC suggests strategic complementarity between the two forms of governance.

To test the hypothesis of strategic complementarity, we employ three variables that measure the thickness of the market at the buyer-year level. First, $S_{i,y}$ is the average number of active sellers for buyer $i$ over all days that the buyer comes to the market in year $y$. Second, $\frac{B}{S}_{i,y}$ is the average buyer number ($B$) over seller number ($S$) ratio for buyer $i$ over all days that the buyer comes to the market in year $y$. Given the number of sellers, this variable also indicates the average number of buyers on the market for buyer $i$. The first two variables jointly measure the number of active traders. Third, $Mvol_{i,y}$ is the logarithm average total volume traded on the market over all days that the buyer comes to the market in the year (measured in metric tons).

The dependent variable, $RT_{i,y}$, equals 1 if buyer $i$ forms an RC in the year, namely, if he/she trades repeatedly with at least one seller for at least 20 times in the year. The regression is set up as

$$RT_{i,y} = \alpha + \beta_1 S_{i,y} + \beta_2 \frac{B}{S}_{i,y} + \beta_3 Mvol_{i,y} + X_{i,y}\gamma + \tau_y + \epsilon_{i,y}, \tag{19}$$

where vector $X_{i,y}$ includes buyer-year control variables, $\tau_y$ contains year fixed effects, and $\epsilon_{i,y}$ is the error term. Control variables include the buyer's total number of days trading in the year, the average daily volume purchased in the year (in logarithm form), and the annual average time of trade (measured in hour-minute and in logarithm form).

Estimation results are reported in Table 6. Variable $\frac{B}{S}_{i,y}$ has a positive and significant coefficient estimated, suggesting that a thicker market fosters the formation of relationships. The volume size of the market, though, has no significant impact on the formation of RC.

Besides, a buyer who visits the market for more days and buys a larger average volume is more likely to form an RC. According to our model, this makes intuitive sense because a more frequent buyer is more likely to be one with downstream obligation and a larger buyer tends to face a larger $\phi^b$, everything else the same. Both indicate a larger quasi-rent from RC.[9]

Taken together, the conceptual model and empirical tests suggest that 1) the formation of relationships alongside a spot market can achieve higher market efficiency than a spot-transaction-only market, namely, efficiency requires the coexistence of RC and spot markets, and 2) the thicker the spot market, the stronger incentive for relationships to form, namely, the more likely that RC serves as a strategic complement for spot transactions.

[9]We also use the buyer's annual total volume purchased as a control variable instead of the buyer's average daily volume purchased. The results are consistent and available upon request.

Table 6—Complementarity between RC and the Spot Market: Probit Regression

| **Variable** | **Coefficient** | **Std. err.** | **z** | **P> \|z\|** |
|---|---|---|---|---|
| Buyer's avg. no. seller ($S$) | 0.001 | 0.02 | 0.50 | 0.62 |
| Buyer's avg. buyer-seller ratio ($\frac{B}{S}$) | 0.07 | 0.02 | 3.72 | 0.00 |
| Buyer's avg. market volume ($Mvol$) | -0.04 | 0.16 | -0.24 | 0.81 |
| | | | | |
| Buyer's no. trading days | 0.03 | 0.001 | 24.89 | 0.00 |
| Buyer's avg. volume purchased | 0.21 | 0.05 | 4.31 | 0.00 |
| Buyer's avg. trading time | -0.36 | 0.18 | -1.97 | 0.05 |
| Year fixed effects | Yes | | | |
| No. observations | 6,309 | | | |
| Log likelihood | -531.59 | | | |
| Likelihood ratio $\chi^2$ | 1,730.34 | | | |
| $Prob > \chi^2$ | 0.00 | | | |

*Note: Buyer's number of 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.

More fundamentally, RC may strategically complement spot transactions, which are more flexible than RC, by providing additional stability to traders and helping address inefficiency caused by the mal-adaptation of spot transactions facing volatile market demand and supply. The insight speaks to Baker, Gibbons and Murphy (2011) who demonstrate the strategic complementarity between RC and formal contracts: RC complements formal contracts, which are more stable than RC, via providing more flexibility to traders. Given that RC lies between markets and formal contracts in the spectrum of transaction forms, it is no surprise that RC is able to complement both forms.

### *E. Strategic Defaults*

In Section V.B, we show that RC price and premium are adjusted under market-wide supply shocks to deter parties from behaving opportunistically, so that the relationship is sustained and the future value of continuing the relationship is retained. However, not all relationships can be or are sustained under shocks. When the spot-market price deviates so much from the mean, it is not hard to see that equation 13 and inequality 15 may not simultaneously hold no matter how the RC price is adjusted. In such cases, an RC is breached or strategically defaulted.[10]

The empirical challenge of detecting opportunistic behavior lies in the difficulty in distinguishing strategic defaults from unwilling deviation from relational traders. Unwilling deviation refers to cases where the defaulting party simply cannot comply with the obligation/promise due to, for instance, a shortage of supply to sellers (Blouin and Macchiavello, 2019).[11]

Our dataset has an advantage in studying strategic defaults because it contains all transactions of all traders in the market, allowing us to see if a buyer and a seller in a relationship do not trade with each other despite that both trade on the market on a given day. The baseline condition we employ to distinguish defaults that occur out of necessity from those that occur for strategic reasons is: 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. We use a probit model to examine the drivers of strategic defaults. Informed by the literature, we employ three sets of drivers: 1) market conditions on $t$, including the number of sellers, the buyer number over seller number ratio, and supply shocks; 2) measures of the relative intensity of the relationship, including the fraction of buyer's purchase out of the seller's sales and the fraction of seller's sales out of the buyer's purchase, as well as a monthly RC index; and 3) the history of default, measured as the cumulative number of defaults as of day $t$. Considering the history of default challenges our assumption in Section IV that a default ceases a relationship. We make this assumption to simplify illustration. We could relax the assumption by following Levin (2003), who shows that allowing RC to restore after 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 RC index ranges from zero to 1.0 and captures the relative intensity of a relationship via two dimensions, namely, the fidelity between the two parties (i.e., the $t/p$ ratio) and the number of interactions for a pair relative to other relationships (i.e., normalized by setting the largest number of RC transactions to be 1 and the smallest number 0). For a monthly RC index, we multiply a monthly $t/p$ ratio by the normalized number of RC transactions per month. The mean value of the monthly RC index, for instance, is 0.13 with a standard deviation of 0.15. In the regression, we use lagged variables of RC intensity to mitigate the concern on endogeneity (i.e., unobserved factors may drive current RC intensity and the default in period $t$).

[10]Mathematically, the DICCs are satisfied if $\frac{p^D-\bar{p}}{p_t-\bar{p}} \geq 1-\mu_t\delta$ with $p_t > \bar{p}$ and if $p^D-\bar{p} \geq 0$ with $p_t < \bar{p}$. The second condition is trivial because the expected downstream price is higher than the expected wholesale price for buyers to remain in business. The first condition may be violated, for instance, if $\mu_t$ is sufficiently small, making the RHS of the inequality larger than the LHS.

[11]In practice, even an unwilling default could harm the relationship. For example, the buyer would have a lower expectation of the relationship's value in providing supply assurance for him/her if the seller does not show up on some business days.

The regression is set up as

$$Default_{ij,t} = \alpha + X_t\beta + W_{ij,t-1}\gamma + \xi H_{ij,t} + \tau_{y(t)} + \tau_{m(t)} + \epsilon_{ij,t}, \quad (20)$$

where vector $X_t$ includes the first set of variables, vector $W_{ij,t-1}$ captures the lagged intensity of the relationship, and variable $H_{ij,t}$ represents the default history between $i$ and $j$ up to period $t$. Vectors $\tau_{y(t)}$ and $\tau_{m(t)}$ are year and month fixed effects, respectively. The error term is $\epsilon_{ij,t}$.

Table 7—Strategic Default: Probit Regression Results

| Variable | Coefficient | Std. Err. | $z$ | $P > \|z\|$ |
|---|---|---|---|---|
| Number of sellers | 0.004 | 0.003 | 1.41 | 0.159 |
| Buyer/seller ratio | 0.021 | 0.011 | 1.94 | 0.052 |
| Positive supply shock | 0.028 | 0.045 | 0.63 | 0.532 |
| Negative supply shock | -0.056 | 0.056 | -1.01 | 0.314 |
| Purchase share last month's avg. | -1.185 | 0.053 | -22.28 | 0.000 |
| Sales share last month's avg. | -0.369 | 0.081 | -4.53 | 0.000 |
| RC index last month's avg. | -0.028 | 0.063 | -0.45 | 0.655 |
| No. past defaults | 0.013 | 0.001 | 13.00 | 0.00 |
| Number of observations | 14,430 | | | |
| Log likelihood | -4,185.01 | | | |
| Likelihood ratio $\chi^2$ | 1,729.11 | | | |
| $Prob > \chi^2$ | 0.00 | | | |

*Note:* The buyer/seller ratio is the ratio of the number of buyers over the number of sellers on the market on day $t$. Supply shocks are defined in Section III.C. The sales concentration of sellers on the day is controlled by adding a Herfindahl–Hirschman index of seller sales. The index equals the summation of squared seller sales shares on the market on day $t$.

Results are reported in Table 7. The likelihood ratio $\chi^2$ of 1,729.11 with a $Prob > \chi^2$ approximately zero indicates good fitness and high statistical power of the model. The coefficients measure the change in the $z$-score for a one-unit change in each predictor variable.

The ratio of the number of buyers over the number of sellers is a significant predictor. Specifically, a higher buyer/seller ratio would increase the likelihood of default. Intuitively, given the number of sellers, a higher buyer-seller ratio implies more competition among buyers. Everything else the same, this likely leads to higher a market price and a stronger incentive for a seller to default and capture a higher spot price instead of sustaining the RC. Shocks have no significant impact on default given RC intensity and default history.

Buyers' purchase share and sellers' sales share are significant predictors. The higher RC intensity may mean a higher RC value defined by equation 11, for instance, via increasing $\mu_t$. Weisbuch, Kirman and Herreiner (2000) and Blouin and Macchiavello (2019) also show that the more valuable a relationship, the smaller the risk of strategic default.

Finally, the history of default is also 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. In the model, a larger number of past defaults likely translates to a lower $\mu_t$.

One might be concerned that, even if both traders are on the market, a seller may simply have too little supply to satisfy the buyer's demand. Thus, we may have under-count unwilling defaults. As a robustness check, we add a second condition to identify strategic default — at the time of buyer $i$'s arrival (using the time of $i$'s first transaction on $t$ as proxy), $j$ still has sufficient stock to fill $i$'s revealed quantity demanded. Though this condition better excludes unwilling defaults, it tends to exclude some strategic defaults because not reserving quantity for a relational buyer until he/she comes to the market can be a sign of strategy default in itself. In this sense, the additional condition may over-count unwilling default. Similar results are obtained and shown in Table G1.

## VI. Concluding Remarks

The market, the firm, and vertical coordination are the three basic forms of economic transactions. In the absence of formal contract enforcement, relational contracting offers another form of vertical coordination to govern economic transactions. It has existed for a long time and has been used widely, but is understudied by economists until recently. When studied, trading relationships are often examined separately from other forms of transactions — researchers implicitly or explicitly assume that the buyer and the seller need a relationship as the only channel to trade. A few studies consider the evolution of relational contracts as spot markets develop and find empirical evidence that the two forms are strategic substitutes.

We present novel micro-level evidence that relationships could be fostered alongside a well-functioning spot market to provide supply assurance to relational buyers, and relationships can be a strategic complement to markets in maximizing efficiency.

The setting is a leading Chinese vegetable wholesale market. We begin the analysis by showing that 1) prices in the market are persistently dispersed, even at the seller-day level, 2) a large number of buyers and sellers conduct repeated transactions, and 3) buyers who conduct repeated trade obtain higher assurance in supply in normal times and under large market-level supply drops. These features are incorporated in a conceptual model that characterizes repeated trade as a relational contract between a seller and a buyer alongside an active and highly competitive spot market.

The model demonstrates that, if the repeated trade is indeed relational, buyers pay their relational sellers a price premium in exchange for the benefit of a more secured supply. The relational surplus is allocated towards the party experiencing less uncertainty (i.e., the sellers), leaving the participation constraint for the buyers binding. Further, the model predicts how RC traders respond to random shocks in market supply in order to sustain the relationship — the RC price varies in the same direction as the market price, while the RC premium varies in the opposite direction. We then explain theoretically why increased thickness of the market, in particular, increased number of traders, may imply higher relational surplus. This hypothesis suggests that relationships and spot markets may be strategic complements to each other.

All the hypotheses are supported by empirical tests. Relational contracting is shown to be an effective way of reducing supply uncertainty and price volatility for traders, salient and pervasive features of agricultural supply chains. Indeed, with growing odds of extreme events worldwide and across industries (Hadachek, Ma and Sexton, Forthcoming), supply disruptions likely become serious for many non-agricultural supply chains, too. Market development alone may not be able to address the issue. We highlight the value of relational contracts as strategic complementarity to markets by providing more stability to spot transactions. This insight echoes Baker, Gibbons and Murphy (2011) who show the strategic complementarity of relationships by providing more flexibility to formal contracts. The shared view is to recognize the general complementarity of different forms of transactions in maximizing efficiency.

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## Additional Summary Statistics

This appendix section provides more information on the wholesale market of interest and repeated transactions observed on the market.

Figure A1 shows a typical scene from the market. The market has multiple trading halls that have similar structures. Inside this particular trading hall, sellers put piles of radish on the ground in front of their trucks. All buyers are free to walk around and talk with sellers on a business day. There is no limit as to the price settled, quantity bought, or how many sellers a buyer may talk to or negotiate with.

When a price is settled by a pair for a certain quantity, the buyer and the seller go to the electronic scale located at the entrance of each trading hall to weigh the products. The weight is immediately recorded in the market's digital system. They would tell the staff at the scale the price they agreed upon and swipe their trading cards, which are effectively debit cards in which they deposit money. Money is transferred immediately, and their personal information and transaction information (price, volume, and time) are recorded in the digital system where we obtain data for this study.

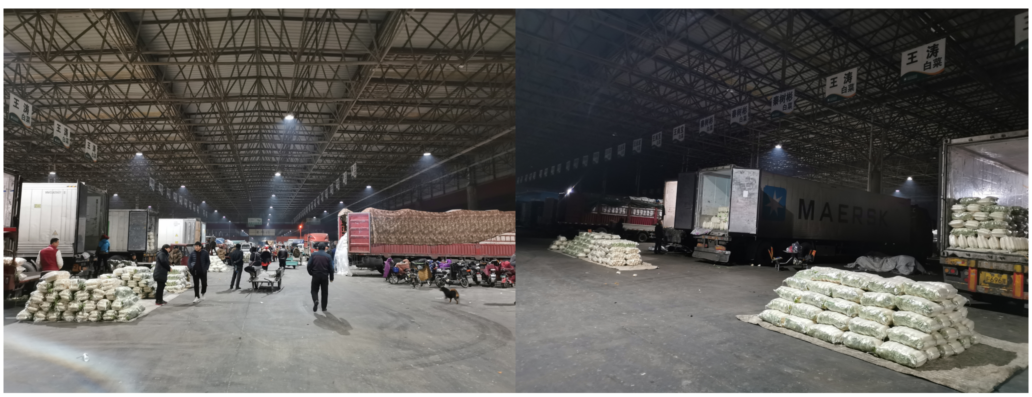

Figure A1. Scenes of The Wholesale Vegetable Market

*Note:* The pictures are taken by the author at the market on December 17, 2019.

Table A1 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) trades 11 (8) days per year. The number of days that a trader visits 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. The total purchase/sales per year also vary considerably across the traders. The largest seller sells as much as 4,502 tons of CC per year. On average, a buyer's daily purchase is 1,761 kilograms, with a large standard deviation of 3,116 kilograms. An average seller has daily sales of 7,850 kilograms.

Table A1—Summary Statistics: Trading Activities

| Type | Variable | Mean | SD | Min. | Max. |
|---|---|---|---|---|---|
| *Panel A: Buyers* | | | | | |
| All buyers (N=3904 ) | 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 |
| *Panel B: Sellers* | | | | | |
| All sellers (N=1396) | 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 |

*Note: SD* means standard deviation, *avg.* means average, *no.* means number of, and *kg* means kilogram.

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-market buyers, varies positively with the market volume traded, reflecting increased (spot) market thickness during the peak trading season of each year. In the meantime, the number of sellers varies, showing similar seasonality.

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 and shows weaker and different seasonality compared with the number of buyers. The ratio contains considerable fluctuation from day to day, too. 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.

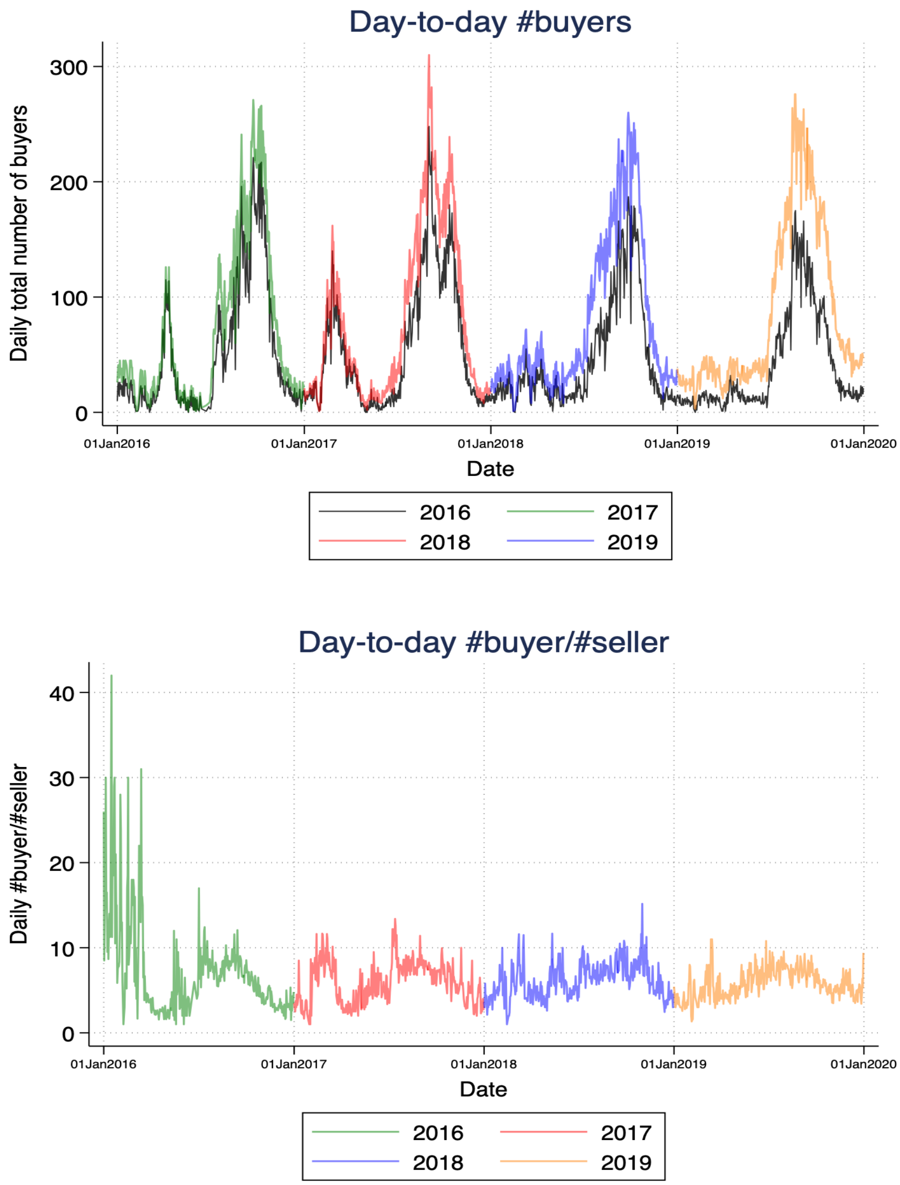


Figure A2. Day-to-Day Fluctuation in the Number of Buyers and Buyer-Seller Ratio

*Note:* The solid black curve in the upper panel indicates the number of nomad buyers on the market and a day, while the colored curves indicate 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 for at least 20 times in a year, namely, the baseline definition of repeated trade in Section III.B. Buyer-seller ratio equals the daily number of buyers divided by the daily number of sellers on the market of CC.

In addition to day-to-day price fluctuation shown in Figure 1, there is considerable seller-day price dispersion. Figure A3 plots prices charged by several sellers over a particular trading day. The green line represents the hourly weighted average market price for that day. The size of each circle corresponds to the relative size of the transaction at the given price. Transaction time and volume do not seem to play an apparent role in explaining the price dispersion we observe.

Browsing over all seller-day plots, one can see that within-seller price dispersion is persistent across sellers and trading days and that it cannot be fully attributed to trading time and volume.[12] As is shown in Section V.A, repeated transactions explain the within-seller price dispersion to a significant extent.

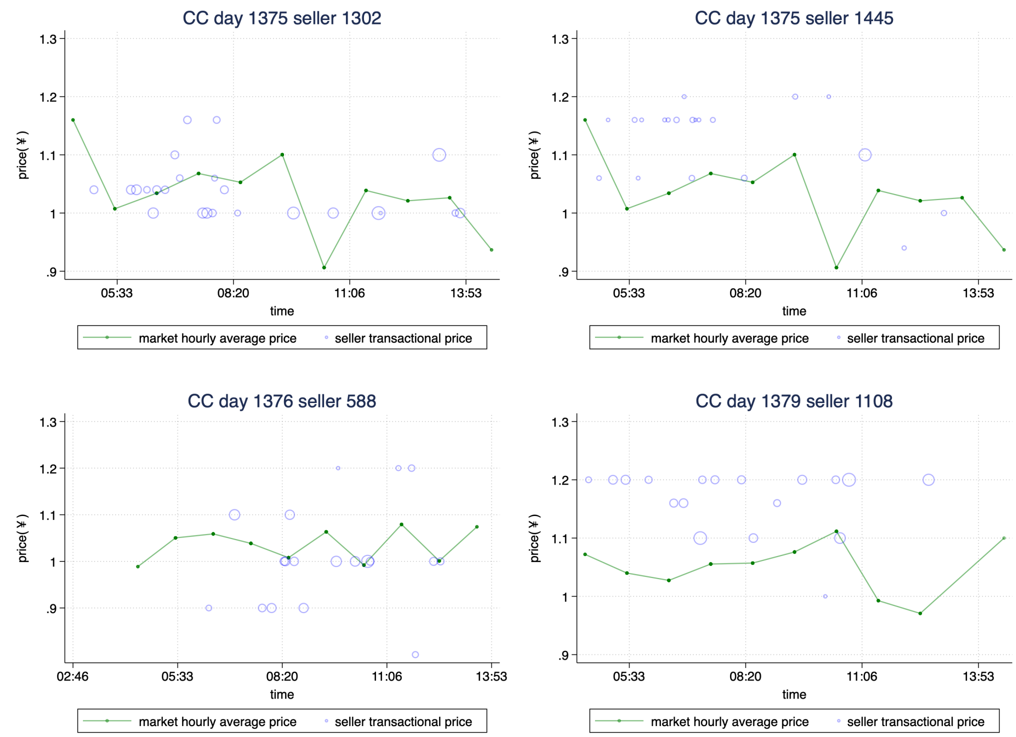


Figure A3. Examples of Seller-Day Price Dispersion

*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.

Table A2 reports test results of equation 2 in Section III.C. In normal times, buyers with repeated trade enjoy higher reliability ratios than nomad buyers as the coefficient of $RT$ is positive. The reliability ratio falls on average when the

[12]Readers may request to see the complete set of seller-day price plots.

market experiences a negative supply shock, suggesting that buyers on average experience a shortage of supply under a negative supply shock.

For buyers with repeated trade, however, the decrease in the reliability ratio is smaller under negative supply shocks. Both effects suggest that repeated trade likely provides supply assurance to buyers in this market. In Appendix C, we provide additional evidence for the supply assurance effect using a sophisticated stochastic frontier model.

Table A2—Reliability & Volatility Ratio Tests

| Dependent variable: | Reliability Ratio | | | | Volatility Ratio |
|---|---|---|---|---|---|
| | Baseline | | Robustness | | |
| | (1) | (2) | (3) | (4) | (5) |
| RT | .083*** | .081*** | .079*** | .075*** | |
| | (.005) | (.004) | (.005) | (.005) | |
| Negative supply shock | | -.084*** | | -.103*** | |
| | | (.007) | | (.007) | |
| RT × Negative supply shock | | .017* | | .023** | |
| | | (.009) | | (.009) | |
| Relationship | | | | | -.046*** |
| | | | | | (.011) |
| Year and month fixed effects | Y | Y | Y | Y | Y |
| No. observations | 144,472 | 144,472 | 144,472 | 144,472 | 27,261 |
| Adjusted $R^2$ | 0.097 | 0.102 | 0.085 | 0.087 | 0.119 |

*Note:* * $p$-value< 10%, ** $p$-value< 5%, *** $p$-value< 1%. The upper and lower one percentiles of the reliability ratios are dropped. In calculating the volatility ratios, we exclude days when the magnitude of market price change is smaller than 5% to mitigate noise in the data. We then trim the ratios by removing the lower and upper one percentiles to eliminate outliers.

## Variance Decomposition

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

Table B1 presents the outcomes from running ANOVA for the full dataset. Trading day and seller identifier explain most of the variance. The key takeaway is that seller fixed effects and volume and timing of transactions only explain 84% of the price variance on the market. There remains considerable price dispersion within a seller on a given day.

Table B1—Variance Decomposition of Transaction Prices

| Years | Source | Seq. SS | Dof | MS | F | Prob>F |
|---|---|---|---|---|---|---|
| *2016-2019* | Model | 39160.47 | 9182 | 4.26 | 106.34 | 0.00 |
| | | | | | | |
| | Seller identifier | 14633.54 | 1394 | 10.50 | 261.75 | 0.00 |
| | Trading day | 23200.15 | 1439 | 16.12 | 402.00 | 0.00 |
| | Trading volume | 1234.62 | 6326 | 0.20 | 4.87 | 0.00 |
| | Trading hour | 92.16 | 23 | 4.01 | 99.91 | 0.00 |
| | | | | | | |
| | Residual | 6843.56 | 170641 | 0.04 | | |
| | Total | 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. *Trading volume* is the quantity traded measured in kilograms. *Trading hour* is the indicator for the hour of a day when the transaction takes place, for instance, during 9-10 a.m.

### Zero Inefficiency Stochastic Frontier Estimation

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

We employ a stochastic frontier technique. Introduced by Aigner, Lovell and Schmidt (1977), the classic Stochastic Frontier Model (SFM) assumes that a producer has a production function $f(z_i, \beta)$ and would produce $q_i = f(z_i, \beta)$ in a world without error or inefficiency. The stochastic frontier analysis assumes that each firm 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 $t$,[13]. Variable $\upsilon_{i,t}$ is independent, identically, and normally distributed with a support of $N(0, \sigma_{\upsilon}^2)$. It captures the effects of unobservable characteristics and measurement errors. The vector $Z_{i,t}$ includes controls for day-of-week, month, year, and time of the transaction.

The buyer's actual amount of purchase is expressed as

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

where $\theta_{i,t}$ 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,

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

Let $u_{i,t} = -\ln(\theta_{i,t})$, 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 not plausible to assume that buyers are rationed each day. In fact, they may purchase according to their demand on a good number of days. The obvious caveat of using the standard SFM is that it assumes each observation is inside the efficiency frontier, namely, there is some degree of inefficiency (rationing) associ-

[13]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, he/she should be able to purchase $q_{i,t}(p_{i,t})$ at the lowest price $p_{i,t}$.

ated with each observation. Thus, the standard SFM is not able to accommodate the case when some observations are efficient.

Introduced by Kumbhakar, Parmeter and Tsionas (2013), the Zero Inefficiency Stochastic Frontier (ZIFS) model 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 $\rho_i$. 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, $N^+(0, \sigma^2_{u_i})$.

The only additional parameter in the ZISF model compared to the standard SFM is $\rho_i$. The statistical identification of this parameter requires non-zero observations of non-rationed days, which is a valid assumption in our context as long as some buyers are not rationed on some days from 2016 to 2019.

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 different across buyers. We restrict the estimation to the sub-sample of buyers who have a $T_i > 200$, with a total of 241 buyers.[14]

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

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

where $\sigma = \sigma_v^2 + \sigma_u^2$, $\sigma_0 = \sigma_u/\sigma_v\sigma$. For brevity, all subscription $i$ on the RHS of this equation are omitted.

We follow one of Kumbhakar, Parmeter and Tsionas (2013)'s approaches and censor the posterior estimates $\check{\rho}_{i,t}$ as follows:

- $\check{\rho}_{i,t} \geq 0.95$: $i$ is not rationed on $t$
- $\check{\rho}_{i,t} < 0.95$: $i$ is rationed on $t$ with a inefficiency score

For those buyer-days with posterior probabilities of efficiency greater than 0.95, we assign an inefficiency score of zero. For buyer-days that have posterior probabilities less than 0.95, we assign them inefficiency scores (i.e., the conditional mean estimator for $u$ for each observation). The inefficiency scores are constructed using

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

the ZISF maximum likelihood estimates with $\rho_i = 0$:

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

Again, the subscription $i$ is omitted for on the RHS brevity. The degree of being rationed is thus expressed by

$$\hat{R}_{i,t} = 1-\theta_{i,t} = e^{u_{i,t}} - 1 \tag{C7}$$

Table C1 reports the estimation results of the ZISF model. Variable, $RT_{i,y(t)}$, is an indicator variable that equals one if buyer $i$ conducts repeated transactions in a given year. Column (1) suggests that buyers conducting repeated trade tend to have a lower probability of being rationed compared with their counterparts. Column (3) further suggests that, if rationed, buyers conducting repeated trade tend to be rationed to a smaller degree.

Restricting the sample to buyers conducting repeated trade, we also check if the percentage of purchase of buyer $i$ that is made through repeated trade and the number of sellers that $i$ repeatedly transacts with affect the likelihood and degree of rationing. Columns 2 and 4 show that the more a buyer purchases through repeated trade the less likely he/she is rationed and the less severe he/she is rationed. The supply security is reduced if the buyer conducts repeated trade with more sellers than fewer.

Table C1—Relationships Provide Supply Assurance (ZISF Estimation)

| | Probb. being rationed | | Avg. percentage rationed | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Panel A: all buyers* | | | | |
| RT | -.181*** | | -.119** | |
| | (.037) | | (.049) | |
| *Panel B: RT buyers* | | | | |
| Frac. repeated purchase | | -.058*** | | -.132*** |
| | | (.021) | | (.055) |
| Number of sellers | | .033*** | | .021** |
| | | (.009) | | (.005) |
| No. observations | 363 | 125 | 363 | 125 |

*Note:* * $p$-value< 10%, ** $p$-value< 5%, *** $p$-value< 1%. *Frac. repeated purchase* is a buyer's fraction of purchase from repeated traders out of his/her total purchase.

### Rationing with Constrained Demand

Being rationed (i.e., supply insecurity) is a major concern for buyers in the wholesale market of interest. At first glance, the concern might be surprising given that the market is competitive, traders search at minimal costs, and each pair of traders are free to negotiate price and quantity. As a result, any buyer should be able to obtain any quantity demanded at a given price along his/her demand curve, making 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, we first 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., there is 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 supply). 3) Each seller faces stochastic arrival of buyers over the day (i.e., uncertain demand). 4) Prices are not posted, but negotiated by each pair of traders for each transaction and are adjusted freely.

The first three features listed above make our market highly comparable to markets of seasonable goods like Christmas gifts and goods with a fixed supply like airlines that employ complex inter-temporal pricing strategies to avoid stock-outs as well as unsold units. Dynamic pricing in those markets has been studied extensively (Carlton, 1978; Deneckere and Peck, 2012; Williams, 2022). The studies show that, due to pre-committed supply and uncertain demand, even if prices are adjusted freely over the course of the trading window, some buyers would be left failing to fulfill their demand, and, of course, some sellers would fail to sell out all inventory. The finding is intuitive by observing, for instance, unfilled flight cabins and passengers unable to get on flights they want from day to day. Buyers not fulfilling their demand, in particular, would be referred to as being rationed or suffering supply insecurity in our context.

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

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

Thus, the demand of a buyer is jointly constrained by his/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 supply and demand of other buyers. Under negative (positive) supply shocks, the residual market supply curve shifts to $S_t^{neg}$ ($S_t^{pos}$).

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 $q_{i,t}^{max}$ however 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 the unit shipping cost, and $\bar{q_{i,t}}$ is 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) to fulfill each day 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 generates a loss for each unit procured. The buyer might still buy some units due to a reputation concern. 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 loss 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 $q_{i,t}^*$.[15] For equilibrium prices higher than $p^D - \tau(q) + r(q)$, the quantity rationed is as large as $\bar{q_{i,t}}$.

As mentioned in Section III.C, not all buyers are concerned with being rationed. Specifically, for buyers selling to secondary-stage markets, a target quantity of supply or reputation may be less relevant.[16]

Figure D2 demonstrates the alternative scenario. The buyer again has a fixed shipping capacity of $q_{i,t}^{max}$ and expects to sell units purchased at $p^D$ in 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 makes 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 $S_t^{neg}$; supply under a negative shock). The wedge between $q'_{i,t}$ and the quantity purchased $q_{i,t}^*$ has

[15]We could set $\bar{q_{i,t}}$ at a price lower than $p^D - \tau(q)$. Shortage of supply would be larger at a given residual supply. The key intuition would hence be strengthened.

[16]Of course, these buyers may as well have a target quantity to procure if they have, for instance, relational buyers in the downstream market or if they simply want to fill the trucks. If so, we should model their demand in a similar way as in the first scenario discussed.

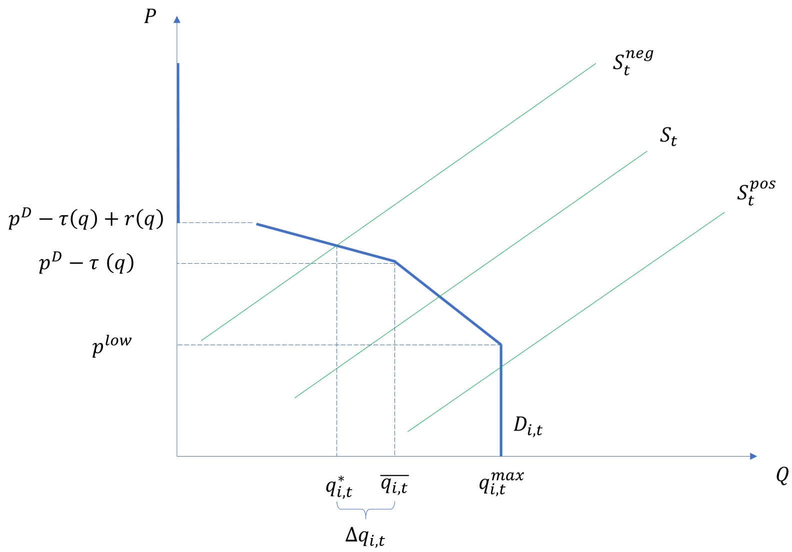


Figure D1. Quantity Rationed for a Constrained Demand and a Competitive Market: Case 1

an interpretation different from $\Delta q_{i,t}$ in Figure D1. This is because no amount between $q'_{i,t}$ and $q_{i,t}^{max}$ is an obligation from the buyer's perspective. The wedge hence does not mean that the buyer is rationed.[17]

What determines the probability of being rationed for a given buyer? As Figure D1 suggests, it is the distribution of the residual supply for the buyer that drives the probability and degree of being rationed. The residual supply is the supply net of supply captured by other buyers on the market. Given the total supply, the residual supply for a buyer tends to fall with a larger number of competing buyers and larger demand of them.

Recall Figure A2, there is substantial volatility in the number and relative number of buyers on the market from day to day. That means, the distribution of residual supply likely has fat tails. There are days when supply insecurity is high and days when supply insecurity is low, or $\phi^b$ is large and small in the conceptual model built in Section IV. Different values of $\phi^b$ indicate different RC surplus according to equation 11.

In summary, being rationed on a competitive market is theoretically possible and does happen in reality for buyers because the supply is pre-determined, the market demand is random, and the demand of some buyers is constrained by the downstream market. In particular, the demand is not a smooth and complete downward-sloping curve, but a curve with kinks and breaks due to the buyer's

[17]The unit shipping cost likely falls in the quantity shipped due to non-trivial fixed costs with 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.

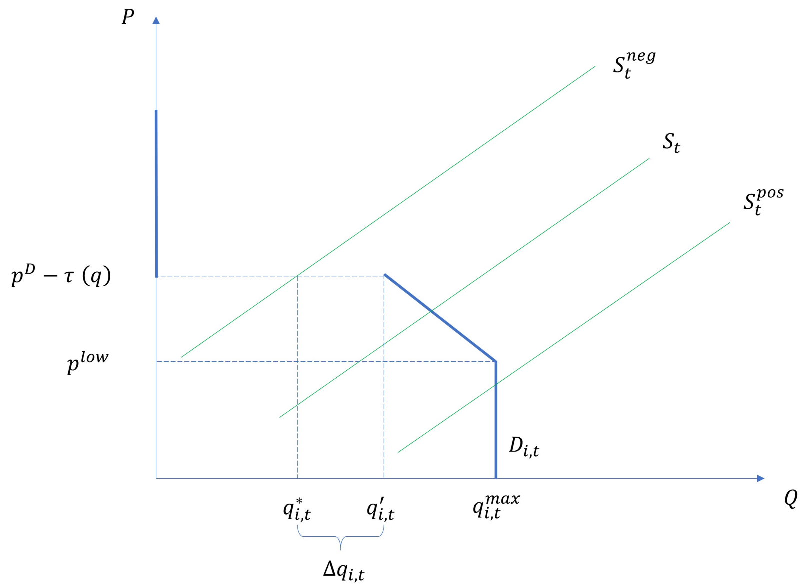


Figure D2. Quantity Rationed for a Constrained Demand and a Competitive Market: Case 2

fixed shipping capacity and a finite downstream price to be obtained by the buyer. A quantity rationed can hence be defined for a buyer as the difference between how much is demanded and how much is procured from the market. Buyers that have downstream obligations to fulfill lose profits if rationed, while buyers without obligations are not rationed. Those with obligations are hence likely to be incentivized to develop RC to assure supply from sellers and avoid profit losses.

## Expected Default Probability

The expected probability of default in period $t$, $\mu_t$, can be derived using the Bayes' Theorem (Macchiavello and Morjaria, 2015). Suppose there are two types of sellers on the market. Some sellers are fully reliable and do not default in any period (i.e., type 1). The probability of this type of seller is $\theta$ on the market, which is common knowledge. The other type of seller may default at a probability of $1 - \lambda$ in a period (i.e., type 2).

There is information asymmetry in the sense that the type is only known to the seller, but not the buyer. With repeated transactions, the buyer updates the probability of the two types of sellers. Whenever an RC is breached, the buyer knows that the seller is type 2.

With $n$ consecutive RC transactions, the probability for the seller to be type 1 is:

$$\theta_n = \frac{\theta}{\theta + (1-\theta)\lambda^n}, \tag{E1}$$

which increases in $n$.

The expected probability of a successful RC transaction in the following period is:

$$\mu_n = \theta_n + (1-\theta_n)\lambda, \tag{E2}$$

which also increases in $n$. As an RC ages or $n$ increases, $\mu$ in equation 11 increases, implying an increasing RC value.

### Price Volatility under Repeated Transactions

Section IV.B suggests that spot-market price fluctuation passes through partially to RC prices. Intuitively, this is because $p_t^{RC}$ is formed based on the expected 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 $\bar{P}_t - \bar{P}_{t-1}$.

$$vol_{ij,t} = \frac{P_{ij,t} - P_{ij,t-1}}{\bar{P}_t - \bar{P}_{t-1}} \tag{F1}$$

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. 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

$$vol_{ij,t} = \beta\ R_{ij,t} + \tau_{y(t)} + \tau_{m(t)} + \epsilon_{ij,t} \tag{F2}$$

where notation follows equation 17.

If RC serves as a cushion against price fluctuation and the price volatility is suppressed for the trading parties that conduct repeated trade, one would expect the sign of the relationship dummy to be negative. Column (5) in Table A2 presents the supporting evidence. The coefficient of the relationship dummy is -0.046, indicating that repeated trade indeed reduces price volatility for the buyer and seller.

### An Additional Robustness Test

We report results from the second regression on strategy default. Compared with the baseline in Section V.E, we add a condition that further trims observations to exclude unwilling defaults from the sample for estimation. This condition, though, likely excludes some strategic defaults from the sample, too. In other words, the baseline condition likely fails to exclude some unwilling defaults, while this additional condition likely fails to include all strategic defaults. Neither definition of default is perfect, but the two samples generate similar results and jointly confirm the key determinants like the history of defaults.

We also replace the RC index by the age of RC and try a different second condition that, when buyer $i$'s arrives, seller $j$ still has not sold out his/her stock. Similar results are obtained, too, and available upon request.

Table G1—Strategic Default: Probit Regression Results - Robustness Check

| Variable | Coefficient | Std. Err. | $z$ | $P > \|z\|$ |
|---|---|---|---|---|
| Number of sellers | 0.005 | 0.003 | 1.55 | 0.122 |
| Buyer/seller ratio | 0.026 | 0.011 | 2.26 | 0.024 |
| Positive supply shock | 0.036 | 0.048 | 0.75 | 0.454 |
| Negative supply shock | -0.083 | 0.061 | -1.36 | 0.174 |
| | | | | |
| Purchase share last month's avg. | -0.972 | 0.057 | -17.13 | 0.000 |
| Sales share last month's avg. | -0.518 | 0.093 | -5.58 | 0.000 |
| RC index last month's avg. | -0.009 | 0.068 | -0.13 | 0.898 |
| | | | | |
| No. past defaults | 0.012 | 0.001 | 12.24 | 0.000 |
| Number of observations | 14,430 | | | |
| Log likelihood | -3,606.24 | | | |
| Likelihood ratio $\chi^2$ | 1,239.45 | | | |
| $Prob > \chi^2$ | 0.00 | | | |

*Note:* The buyer/seller ratio is the ratio of the number of buyers over the number of sellers on the market on day $t$. Supply shocks are defined in Section III.C. HHI stands for the Herfindahl–Hirschman index and equals the summation of squared seller sales shares on the market on day $t$.