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

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Selected Paper prepared for presentation at the 2022 Agricultural & Applied Economics Association Annual Meeting, Anaheim, CA; July 31-August 2

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

By YUJING SONG*

Stable trading relationships based on informal agreements represent an important but little understood governing form of transactions. Using detailed transaction-level data of a large wholesale vegetable market in China, this paper provides evidence on the persistence of relationships in a well-functioning, almost friction-less market. Relationships serve as informal price insurance for the trading parties — price volatility is smaller in relational transactions. Buyers who have stable trading partners obtain greater supply assurance, while sellers are able to extract a premium. Theses benefits appear greater in longer and more intense relationships.

I. Introduction

Economic transactions are governed by three main forms: the market, the firm (hierarchy), and long-term relationships (Williamson, 2005). Among the three governing forms of trade, the market is most familiar: prices coordinate the decentralized choices of anonymous parties that interact through short-term enforceable contracts and thus play the key role in allocating resources and governing adaptation. The firm can sometimes replace prices as the mechanisms through which resources are allocated and adaptation needs met. In between markets and firms sits a variety of intermediate (sometimes hybrid) governance forms of which long term relationships are an important special case. Studies have found that relationships - observed as repeated trade between agents - account for a large share of transactions, especially in developing countries.[1] Despite the rising awareness of their prevalence, relationships remain the least studied form of governance.

Are relationships temporary arrangements destined to dissolve into either markets or firms, or do they represent a stable governance form? Theoretical models have predicted that when outside options improve (e.g., as markets develop), making a particular reciprocal agreement less attractive to one party, the agreement 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. On the other hand, it is argued that markets and relationships could also be strategic complements — a relatively liquid and well-functioning market might be needed for relationships and firms to function

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[1]Macchiavello (2021) gives a thorough review of studies concerning economic relationships.

properly (Macchiavello, 2021).

Little is known about the answer empirically. Existing empirical studies focus on relationships in institutionally weak environments where markets either do not exist, or do not function well, and firms are small in size and poorly managed.[2] The value of forming relationships is not too puzzling in such settings: the risk of delivery failure and delinquent payment is high (Macchiavello and Morjaria, 2015), agents face high search cost in locating trading partners (Rudder, 2020) and are in lack of credit provision to enable short-term financing (McMillan and Woodruff, 1999), and relationships are relied upon to overcome these frictions and/or to discipline opportunistic behavior.

Could relationships emerge and sustain when markets are well-functioning? If so, what are their values? In this paper, I provide evidence of persistent relationships in a well-functioning market. The market is well-functioning in the sense that the flow of information is free and transparent, and prices play the key role in allocation. The pool of potential trading partners is large, and there is little or no risk in the other party's fulfilling payment or delivery obligations. In such markets, one would naturally think that trade is anonymous and there is no room for relationships to be favorable. I rationalize the coexistence of relational trade and anonymous market exchange by measuring the value of relationships. Specifically, I show that the motivation for relationship formation lies in mitigating uncertainty and volatility, which is inherent in developing economy supply chains (Collier and Gunning, 1999) (Asker, Collard-Wexler and De Loecker, 2014), and noticeable in many western supply chains, especially those for agricultural products. Well-functioning markets are insufficient in overcoming such structural supply chain inefficacy. When supply is volatile and agents face persistent price and quantity risk, relationships provide more stability than spot market exchange. The relational contracts embedded in the relationships are essentially insurance contracts for both price and quantity.

The market under scrutiny is a large wholesale market of fresh produce in China. The total yearly trading volume is above 3 million metric tons, one of the highest among all produce wholesale markets in Asia (reference is in Chinese, need to figure out how to add). More than 300 varieties of products are transacted year round. The features of the market are all typical for wholesale markets in developing countries — highly homogeneous products, frequent trade, a large number of wholesalers, free and transparent information flow. Starting 2009, all transactions in the market are recorded through an digital trading system, in which identities of the traders are recorded in the form of a market specific trader ID, which is reliable over time. All transactions feature on-site delivery and immediate money transfer. Thus, there is no risk in delivery or payment, and credit provision is not needed.

[2]A large empirical literature documents the prevalence of relationships/relational contracts across settings (Greif (1993); Bigsten et al. (2000); Fisman (2001); Fafchamps (2004)) — see Gil and Zanarone (2017) for a recent review.

I obtained (partial) access to the proprietary database of real-time transactions with trader IDs and conducted three rounds of field interviews in the market. The unique dataset has two critical advantages over prior studies. First, I am able to measure relationship for each pair of traders. Second, our dataset covers a much larger number of traders and much higher-frequency transactions. Three stylized facts captured attention and lead to my query. First, prices are significantly dispersed on a single day. In particular, the prices an individual seller quotes on a single day are dispersed, even after controlling for i) volume of the transaction and ii) time of the transaction. Second, repeated trade is pervasive in the data. In field interviews, traders claim that they have stable trading partners – go-to sellers for buyers and loyal customers for sellers. Third and most interestingly, sellers charge their relational buyers a price premium. On average, buyers with whom they have a relationship are charged 3-6% more than their anonymous counterparts.

To rationalize these stylized facts, I first set up a conceptual framework that is based largely upon the theory of relational contracts. To rationalize these stylized facts, I first set up a conceptual framework that is based largely upon the theory of relational contracts, the core of which lies in the dynamic incentive compatibility constraintsLevin (2003). The model captures the central tradeoff between between trading on spot market and trading via RC — the former provides flexibility, while the latter, stability. The model provides several testable hypotheses.

The empirical results confirms all hypotheses. Prices are more stable in relationships. On average, price volatility is lower compared to the whole market. When supply drops unexpectedly, price increase is less in relational transactions; when supply becomes unusually abundant, buyers are willing to compensate their relational sellers by paying a slightly higher price. Buyers obtained higher security in supply via engaging in relational activities. There is a significant inverse relationship between the intensity of RC activity of the buyer and the frequency and magnitude of rationing she experiences.

Related Literature. — This study addresses the empirical literature on trading relationships. Previous studies have discussed the value of relationships when markets do not function well. Poorly functioning markets increase the demand for relationships even when exchanging simple goods – the transaction might need to bundle the exchange of other services that are important due to other market failures.(Macchiavello (2021)) Two common services are the provision of credit/prepayment/relaxation in financing terms (McMillan and Woodruff (1999), Antras and Foley (2015), Ghani and Reed (2019)) and the provision of supply/delivery assurance (Macchiavello and Morjaria (2015), Ghani and Reed (2019)). Another important consideration of forming relationships is to reduce search cost in environments where locating trading partners is costly (Rudder 2022). Our results, on the other hand, show that when a competitive market based on spot transactions exists, relationships still emerge and be sustained due to supply chain volatility.

Relational trade is not directly observable. Previous studies have been relying on cross-sectional survey evidence (McMillan and Woodruff (1999); Banerjee and Duflo (2000)), (panel) survey data as well as industry and firm reports (Macchiavello and Miquel-Florensa (2018) and Macchiavello and Morjaria (2021)) to measure relational practices. With the systematically recorded transactional data, our study uses repeated trade as a direct proxy. A few studies also use transactional data (Antras and Foley (2015), which use transactions of a single firm; Macchiavello and Morjaria (2015), which uses export custom data). Yet our data is of much higher frequency and higher fidelity. The data contains identities of the two trading parties and real-time transaction prices for which traders have no incentive to misreport, as cash transfers are based on the prices reported. Such data is (extremely) rare, and exempt, to the largest extent, from measurement errors.[3]

In the theoretical literature, Kranton (1996*a*) develops a model in which the choice of governance forms are strategic complements but interactions between organizational forms are not possible. Empirically, the finding of co-existence of two governance forms is not new (e.g., Weisbuch, Kirman and Herreiner (2000), Hendershott et al. (2020)). None of these studies explain the findings with the theory of relational contracting. In most existing RC studies, the two governance forms do not co-exist. I present theoretical support and empirical evidence of the coexistence of two governance forms in equilibrium. The direct comparison between the two can help identify spot market frictions and improve understanding of relational trade.

The rest of the paper is organized as follows. Section I describes the market, the data, and the stylized facts (price dispersion, relationship characteristics, and price premium). Section II introduces the conceptual framework and derives testable predictions. Section III presents the empirical results and provides a discussion of the findings. Section IV offers concluding remarks and policy implications. Additional results, robustness checks, and further information on the data are available in the online Appendices.

II. Institutional Background and Data

This article is a case study of a massive wholesale produce market in China. This section describes the market, and introduces the data. Evidence of significant (within-seller) price dispersion and repeated trade is presented. The characteristics of the relationships are summarized. Using simple regressions, I show that

[3]Macchiavello (2021) raised a concern in the review of RC studies that repeated trade should not be directly recognized as relational trade. Yet if direct measures of the temptations to deviate were to be observed in the data, much can be learned about the relational nature of trade. Since I am on this track, I adopt a similar approach in measuring relationships as Macchiavello and Morjaria (2015) and use later empirical findings to convince readers that the repeated trade is indeed relational trade in our setting.

relational transactions feature a price premium.

A. The Market

Wholesales market are a dominant channel through which fresh produce products are marketed, especially in developing economies. In 2019, over 70% of fresh produce in China was traded in wholesale markets before being transported downstream to domestic and foreign consumers.[4] At first glance, these markets are highly competitive — products are highly homogeneous, the numbers of sellers and buyers are large, and information flows freely and transparently. Standard search models (e.g., Diamond (1989)) predict that in such market environment, buyers sample sellers according to some rule. All sellers are anonymous and are searched with equal probability. There is no memory of where favorable opportunities were found in the past.

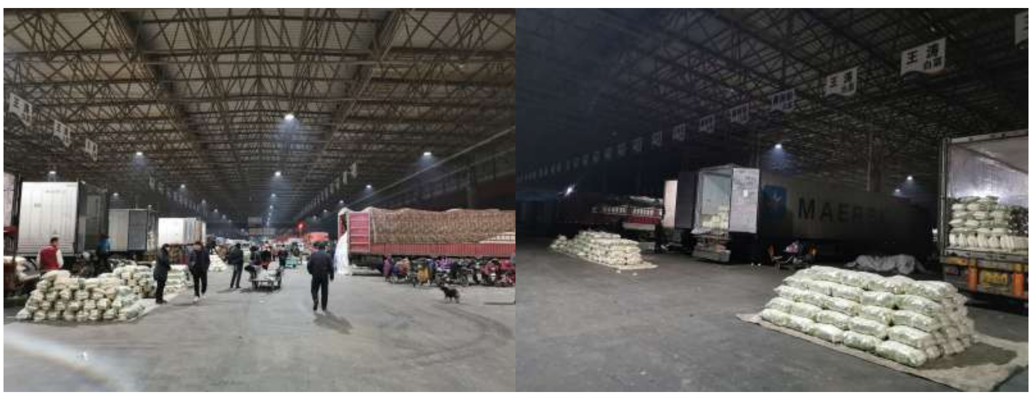


Figure 1. The Wholesale Market

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

As one of the largest wholesale vegetable markets in China, this market is a primary-stage wholesale market where sellers connect directly to the farm gate, as opposed to secondary wholesale markets where products come from an upstream, often larger-scale, market. The products are drawn from multiple production regions all over China, of which varieties vary across seasons. The market opens daily early in the morning (4-5 a.m.). According to Gao (2019), one of the market managers interviewed, most products are sold before noon on a majority of days. Like in most wholesale markets in developing countries, prices are not posted and are based on transaction-specific negotiation. Prices are all FOB prices in the sense that buyers bear downstream shipping costs.

[4] 2019 Annual Report, Ministry of Agriculture and Rural Affairs of China.

B. Data

The analysis of relationships in this market draws on 4 years of (unbalanced panel of) transactions for two commodities, Chinese cabbage and cauliflower. The dataset is extracted from a proprietary database of the market, which is confidential and has not been previously released for any public or private use. Since 2009, each transaction taken place in the market is recorded through its digital trading system.

The unique dataset describes daily transactions through five variables: (1) date and time (specified to second), (2) identities of the buyer and seller, (3) name of the commodity, (4) quantity (in kilogram) and (5) price (in RMB). The identities of the buyer and the seller are marked through a 9-digit market-specific ID number. Such data is rare in the literature, and I know of no other empirical study of trade relationships that use systematically recorded, transaction-level administrative data with known trader identities. In the following analysis, these data are complemented by field observations and interviews with traders, market administrators and local authorities conducted in the summer and the winter of 2019, which provided important context regarding the transaction process.

The first salient feature revealed by the data is the high volatility in supply and in market price. After accounting for seasonality of the product, supply is still subject to random ups and downs. A regression of the weekly average price on week and year dummies explains around 60 percent of the variation in prices.[5] Figures 2 and 3 document the fluctuation in market total trading volume and market weighted average price for the Chinese cabbage (CC) and cauliflower (CF), respectively.[6]

The volume of CF experienced a dramatic drop in 2018, mostly caused by a demand shock. The increase in demand for high-quality cauliflower (under a different commodity name) affected the demand for regular cauliflower, according to Gao (2019). To avoid identification complexities to the greatest extent, I use CC in the following analysis. Summary statistics and empirical results for CF can be found in the online Appendix. Two other reasons for choosing CC is that i) the peak season of CC is in the middle of the year, while that of CF are cut into two years, and ii) CC is more perishable than CR, adding to the validity of the independent trading days assumption.

The dataset of CC encompasses from 2016 to 2019, and consists of 178,022 transactions. CC is sold in bulk with no pre-packaging. Although the shelf-life of CC varies across different end markets, it is considered to be extremely perishable at the wholesale stage, to the extent that overnight storage is rare. The peak season usually starts in June and ends in November, as panel A of Figure 2 shows.

[5]In the online Appendix.

[6]Because some quotes may be misreported, leading to extreme estimates, I trim the data by removing transactions with prices below the 1th or above the 99th percentile of the price distribution on each trading day.

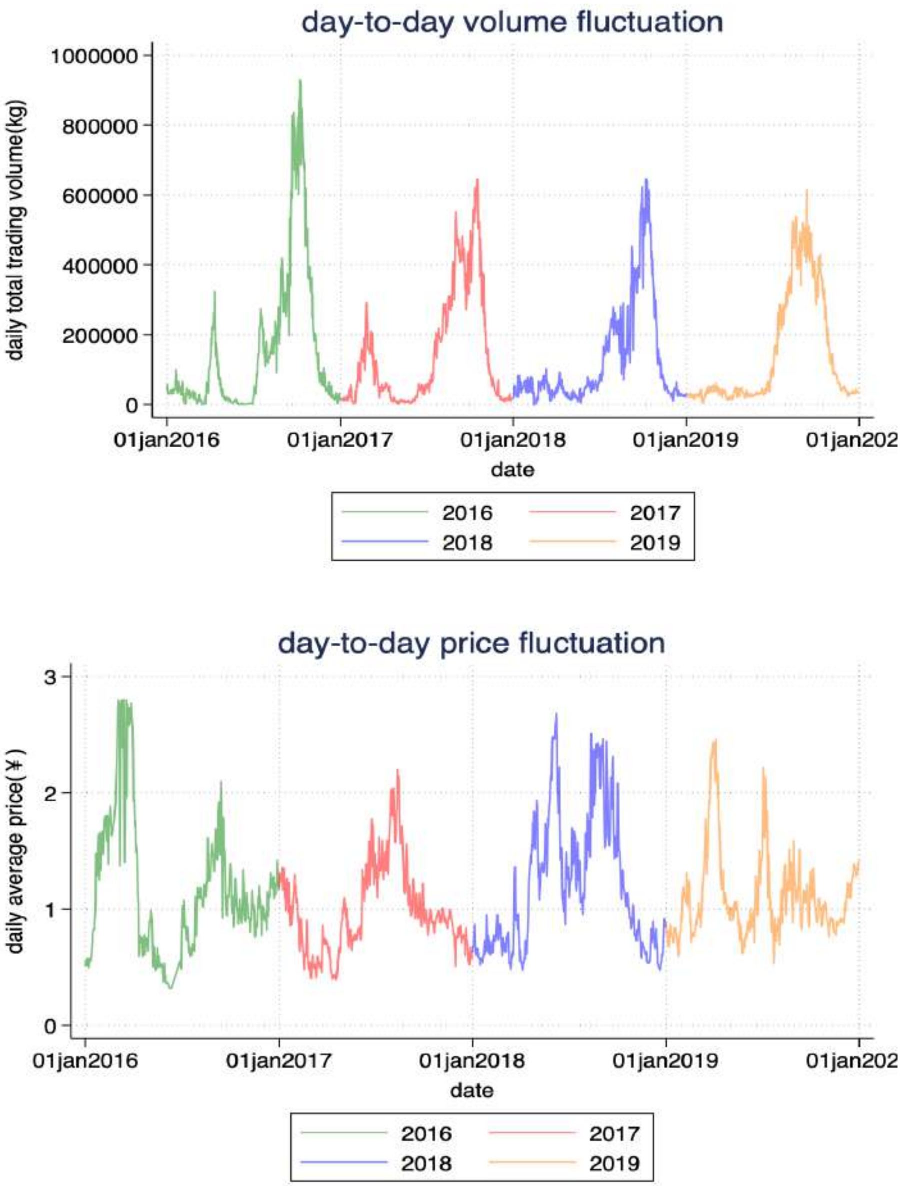


Figure 2. Day-to-day fluctuation in trading volume and price (CC)

The concern for inter-temporal arbitrage and quality heterogeneity (and resulting product differentiation) is minor, if not negligible. Thus, trading days are treated as independent and quality of the product brought to the market by each single seller is considered to be of uniform quality.

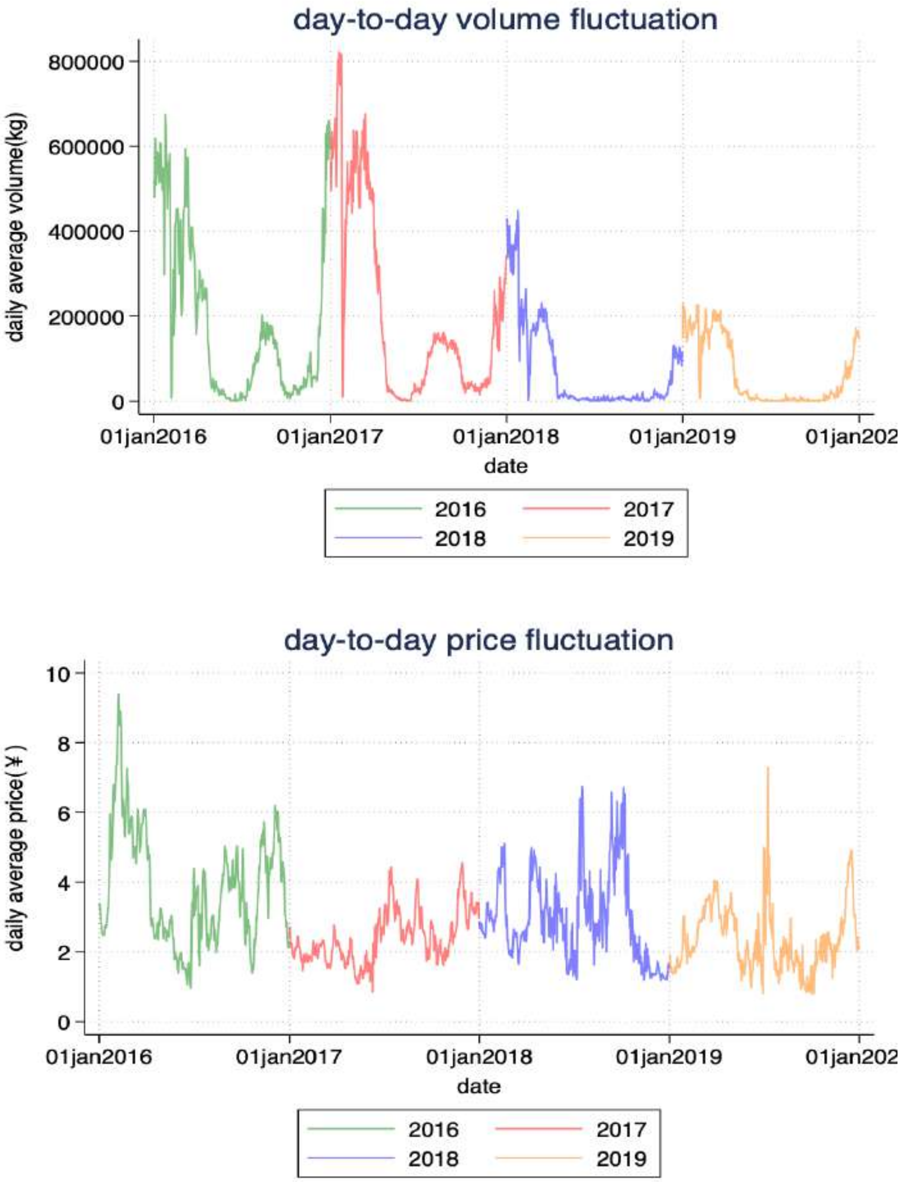


Figure 3. Day-to-day fluctuation in trading volume and price (CF)

Table 1 reports summary statistics for variables at trading day level. Daily market trading volume is as high as 1930,517 kg, and as low as 56 kg. The average transaction size is 1156 kg, with a majority of the transactions lying between 800 to 1400 kg. The numbers of buyers and sellers vary across seasons, while the ratio of the two is relatively consistent. The daily volume-weighted average price has a mean of 1.12 and a standard deviation of 0.49. The range of trading-day level variables are very wide, which is due to the fact that transactions are scarce during off seasons. There are days when there is only one single transaction. It is thus reasonable to focus the empirical analyses on peak/high seasons.

Table 1—Summary statistics - trading day

	Chinese Cabbge (Obs: 1430 days)			
Variable	Mean	Standard Dev.	Min.	Max.
Total trading volume (kg)	144,634.90	173,476.00	56.00	930,517.00
Avg. price (¥(RMB)/kg)	1.12	0.49	0.32	2.80
Number of transactions	125.11	131.18	1.00	525.00
Avg. transaction size (kg)	1156.04	303.15	56.00	16,271.00
Number of buyer	79.42	71.48	1.00	316.00
Number of sellers	12.78	10.11	1.00	56.00
Seller HHI	0.24	0.23	0.03	1.00
Buyer-Seller ratio	6.18	3.28	1.00	42.00

Note: Trading days are calendar days with at least one transaction of CC. All variables are trading day level variables. Average transaction size Seller HHI refers to

Most buyers and sellers are professional traders who have been in the business for years. The dataset does not contain information on their origin or occupation. According to Liu (2019), another market manager interviewed, about 80% of the sellers collect vegetables directly from smallholder producers, while the majority of the remainders owns a large-scale commercial farm. There are more buyers than sellers, and buyers are more heterogeneous in the role they play in the supply chain. Approximately half of them sell to a downstream wholesale or retail market that is much smaller in size, while about 30% procure for supermarkets and the rest procure for restaurants or canteens. Table 2 reports descriptive statistics of their trading activities. I distinguish those who, on average, visit the market to purchase/sell CC more than 20 times in a year from the rest of the sample and categorize them as regular traders.

C. Price Dispersion

This market represents a kind of economic paradox in the sense that, at first glance, one might conclude that it is a vigorously competitive market: there are many buyers and sellers, frequent trades, relatively homogeneous products and low entry barrier if any. Yet the data reveals strong and persistent price dispersion for these homogeneous goods, a feature not reflective of a competitive market.

In addition to market-level price dispersion, a more striking stylized fact is the significant price dispersion "within" each individual seller. While inter-seller price

TABLE 2—SUMMARY STATISTICS: TRADER'S TRADING ACTIVITY

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

Note:

dispersion could potentially be attributed to product heterogeneity across sellers, why a single seller charges different prices on a given day remains unexplained. Figure 4 documents stylized fact of large seller-day coefficient of variation in prices.

To further illustrate, examples of seller-day price dispersion are shown in Figure 5. The figure plots the price of each transaction an individual seller made over the time of the transaction on a trading day. The green line represents hourly weighted average price in the market for that day. The size of the circles correspond to the relative size of the transactions. Apparently, transaction time and volume is not playing a significant role in causing prices to be dispersed. Interested readers can check the online Appendix in which all seller-day plots are given, to see that within-seller price dispersion is persistent across sellers and trading days, and that it cannot be attributed solely to time and volume.

D. Relationships

Economists have long suspected that relationships between agents might be important for us to understand price dynamics in various markets. Wilson (1980) finds that long-term bilateral exchange arrangements explain, to a large extent, the price dynamics in the New England fish market. Studies of financial mar-

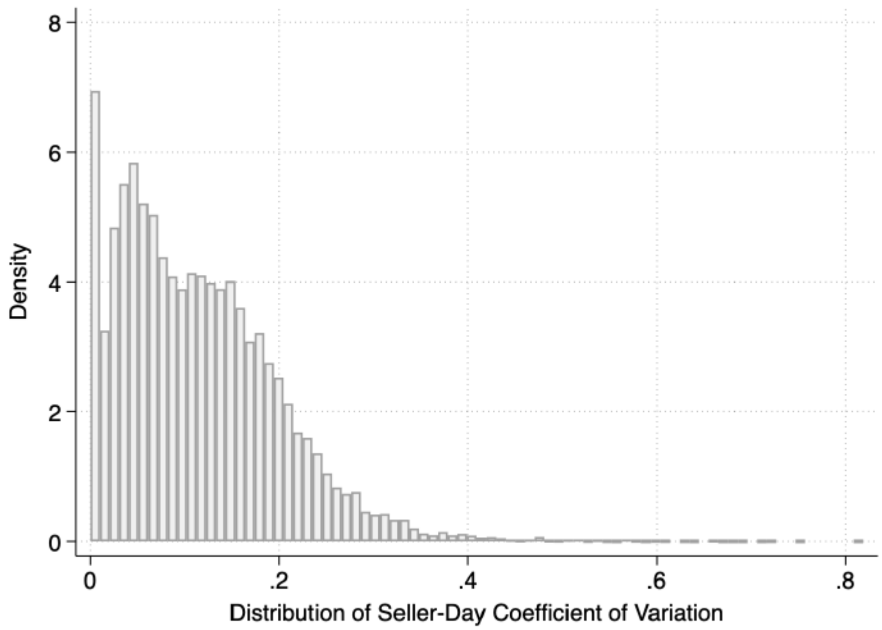


FIGURE 4. DISTRIBUTION OF SELLER-DAY COEFFICIENT OF VARIATION

Note:

kets (e.g., Di Maggio, Kermani and Song (2017)) show that trading relationships prove essential in explaining different pricing behavior. Going along this path, the existence of relationships help explain why a decentralized market where the central assumptions of perfect competition are present should exhibit a stable daily dispersion of prices.

Existing studies of relational contracts (henceforth, RC) adopt various approaches to define active relationships. Following Macchiavello and Morjaria (2015), I construct the baseline sample of relationships by finding sellers and buyers that repeatedly trade with each other. Specifically, a relationship is active if the two parties transacted at least 20 times in a year.[7] The 20-day cutoff is chosen to distinguish between established relationships versus anonymous exchange. In addition to this criterion, I construct a "trade-present" (t/p) ratio to characterise the relative fidelity of each buyer-seller pair. The ratio equals to *the number of trades* (t) between a buyer and a seller over *the number of days when both of them are present* (p), and will be used to in later analyses. Figure 6 plots the t/p ratio over t, number of trade days. Each dot represents a buyer-seller

[7]The cutoff in Macchiavello and Morjaria (2015) is 20 times in the 20 weeks before the violence. The peak season of CC usually lasts 5 months, a little more than 20 weeks, so I adopt a similar cutoff here.

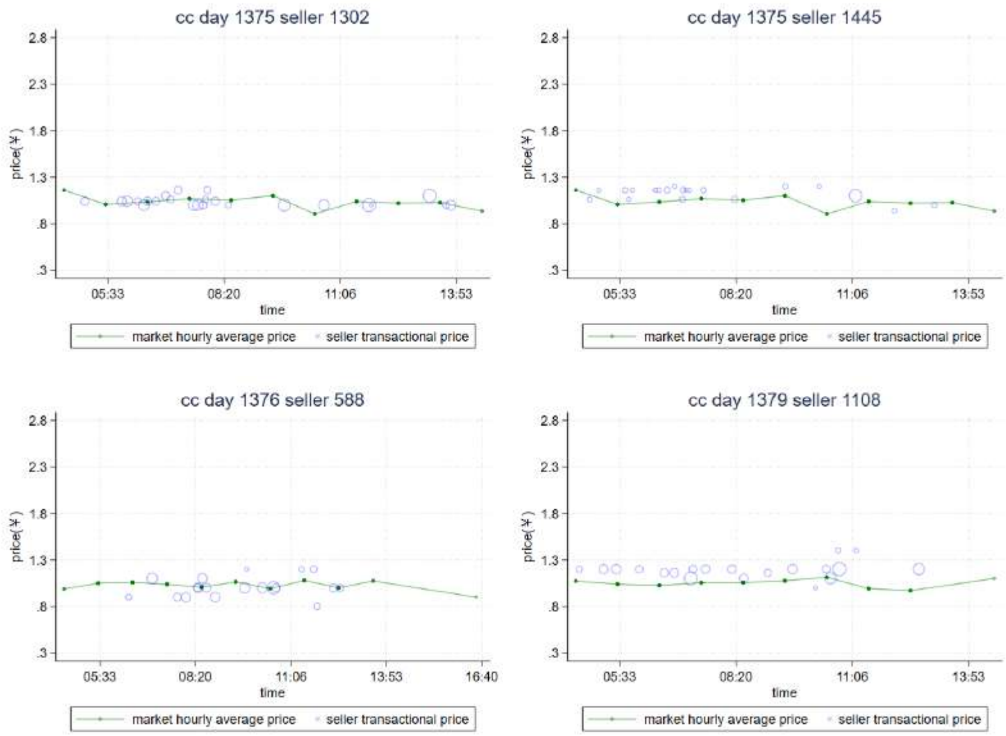


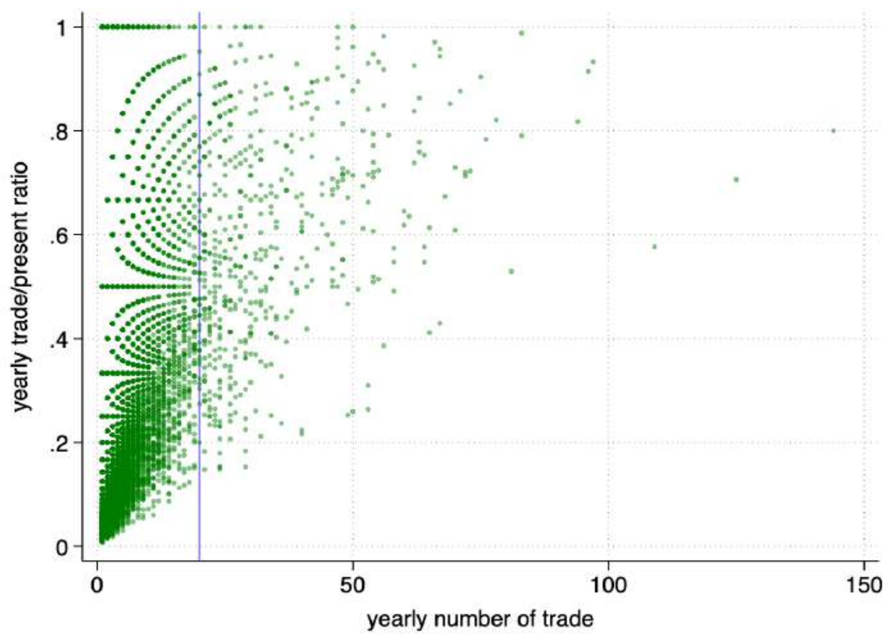
Figure 5. Example of Seller-Day Price Dispersion

Note:

pair. Dots to the right of the blue line are pairs between which a relationship is active for at least one of the four years. A battery of sensitivity checks will be conducted for each later analysis involving the baseline cutoff.

Table 3, panel A reports descriptive statistics for the relationships in the baseline sample. In total, 537 relationships existed for some portion of the four-year data period.[8] The length of the relationship refers to the number of years the relationship is active. The average relationship had 34 transactions per year, and traded 62,041 kg of cauliflower per year. The most intense relationships had 144 trades per year. In the four year period, the longest relationship observed lasted 1,236 days, and likely continues. The t/p ratio ranged from 0.15 to 1, with the average being 0.59. Buyers on average had fewer than two relationships, while sellers had more than nine relationships.

[8]A buyer-seller pair could have an active relationship in one year but not the other year. For example, the buyer and the seller could be seen in the data in 2016, but their relationship might not be established until 2017. On the other hand, a relationship could break down at some point, i.e., the repeated trade discontinue.



Note:

FIGURE 6. t/p RATIO VERSUS NUMBER OF TRADE DAYS

TABLE 3—SUMMARY STATISTICS: RELATIONSHIPS

Variable	Obs.	Mean	Standard Dev.	Min.	Max
Panel A: Relationship characteristics					
Number of trades per year	537	33.7	15.7	20.0	144.0
Trading Volume per year (kg)	537	62,041.3	56,385.8	1,618.0	544,423
Number of days both are present per year	537	62.8	31.6	21.0	201.0
Yearly t/p ratio	537	0.59	0.21	0.15	1.00
Length (in days)	467	160.3	205.6	21.0	1,236.0
Frequency (avg. time-gap between two subsequent transactions)	537	4	3	1	14
Panel B: Number of relationships per buyer and seller					
Number of relationships per buyer	352	1.52	0.89	1	5
Number of relationships per seller	59	9.1	8.06	1	35

E. Price Premium

Upon defining relationships, a natural starting question to ask is: are prices different between relational (relationship-based) transactions and anonymous transactions and if so, by how much? The theory of RC tells us that if a relationship is feasible, then there exists an invariant RC which is optimal and gives any division of the total surplus available (Board, 2011). How surplus is allocated depends on the relative slackness of the contractual parties' IC constraint. One obvious benefit of trading with a stable partner is to save costs, in the form of search cost, freight and time cost, cost of planning, etc (Macchiavello and Morjaria, 2015). Di Maggio, Kermani and Song (2017) find evidence in the OTC corporate bond market that bilateral inter-dealer relations lower markups significantly; Gallegati et al. (2011) show that buyers who have a relational seller obtain systematically lower prices in the Ancona wholesale fish market, both are evidence of relationships saving costs and generating surplus. Startz (2016), on the other hand, shows that Nigerian importers of consumer goods pay a price premium to induce good behavior from suppliers.

Based on my field interviews, buyers who establish relationships enjoy the privilege of ordering in advance, which saves the cost of search and inspection, and secures supply. In obtaining this privilege, it is possible that the buyer pays a contracting premium, analogous to an efficiency wage. The premium must be large enough that the seller prefers to behave honestly — satisfying the buyer's need with fair price and quality product, and receiving the expected stream of future rents — rather than cheating and losing the buyer's business.

To test if a premium exists, I use a regression to explain within seller price dispersion, and add to it the indicator for relationship. The dependent variable is the transaction price between seller i and buyer j on day t, $P_{ij,t}$. On the right hand side of the regression, $Z_{ij,t}$ is a set of explanatory variables that might affect the seller's pricing for a single transaction, which includes hour dummies, and controls for the relative importance of the transaction to the buyer and to the seller — share of this transaction in seller i's total sales on day t, and share of this transaction in buyer j's total purchase on day t. $\theta_{j,t}$ is the seller-day fixed effects. The relationship dummy, $R_{ij,t}$ equals one if the transaction is characterized as relational, i.e., the buyer i and the seller j are bound by a relationship on day t.

$$P_{ij,t} = \alpha + \beta R_{ij,t} + \gamma Z_{ij,t} + \theta_{j,t} + \epsilon_{ij,t} \tag{1}$$

Across all specifications, the coefficient of the relationship indicator is positive and significant. Figure 7 shows preliminary evidence that the premium is not sensitive to the cutoff in defining relationships. Results of a complete series of robustness checks and the whole set of regression results are presented in the Appendix. Economic significance: this premium echos a 3-5% premium paid by relational buyers/charged to relational buyers. One thing to note is that the adjusted R^2 increases when the relationship dummy is added to the regression, indicating that relationship is a significant contributor to (within-seller) price dispersion.

Motivated by the stylized facts and to guide the empirical strategy, I set up a

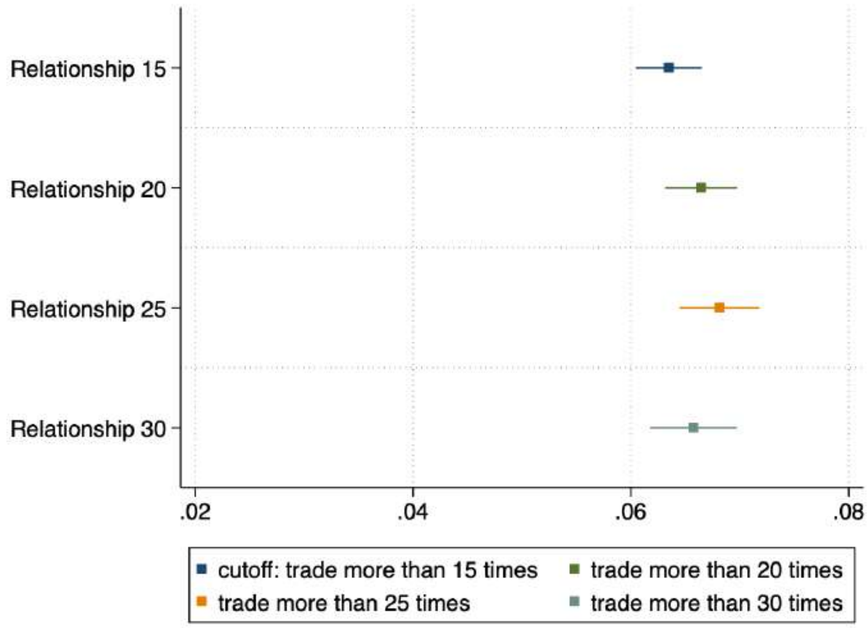


Figure 7. Price Premium in Relational transactions: Preliminary Robustness Checks

conceptual framework in the next section.

III. Conceptual Framework

I provide a characterisation of the self-enforcing trading relationships through a conceptual model. The model dispenses with unnecessary details to illustrate the basic intuition of a relational contract between a vegetable wholesaler (seller) and a buyer. The setup of the model matches qualitative features of the market under consideration. The objectives of the model is to rationalize the stylized facts revealed by the data, and derive testable hypotheses to be tested in the next (empirical) section.

Unlike in existing RC studies where relationships are modeled independently, this framework accommodates relationships alongside an active, well-functioning spot market. Similar two-tier market structures have been documented in many contexts, such as perishable agricultural commodities, advertising, and diamond. Fafchamps (2010) provides an overview of such markets in developing countries. The idea of two-tier market has also been applied to labor markets by Shapiro and Stiglitz (1984). Kranton (1996*a*) contrasts a relation-based market with impersonal exchange and shows that the former can be an equilibrium, though the latter is in general more efficient. Macchiavello and Morjaria (2015) takes the existence of direct relationships as given and does not explain the coexistence of relationships and a spot-market. My model, instead, takes an active spot market as given and shows that relational trade tends to coexist in equilibrium.

The basic intuition of the model is simple. To explain the emergence of relationships in a well-functioning market, Traders choose freely whether to form relationships or to participate in the spot market (anonymously). There are both benefits and costs of forming direct relationships. I assume that the major benefit for the buyers is to get secured supply, and for the sellers, to get secured demand.[9] The cost is two-fold. First, relational traders forgo the opportunity to capture extra profits from price volatility. Second, once RC is breached (defaulted by the other party), they face a higher likelihood of being rationed than "routine" spot market participants. As one of the model's extensions, I allow that the buyer allocates quantity traded to engage in both the spot market and relational trade (given a target quantity of purchase) to tradeoff some security for flexibility.

The model draws heavily on the theory of RC, the core of which lies in Dynamic Incentive Compatibility Constraints (henceforth DICC) (Macchiavello, 2021)

$$(U_{t+1} - U^0_{t+1}) \geq \pi_t \tag{2}$$

where U_{t+1} denotes the net present value of the payoffs from continuing the relationship from time $t+1$ on, and U^0_{t+1} is the value of outside option. Following the literature, I assume that one failure of relational trade leads to termination of the relationship with probability one, which is the worst punishment (Abreu, 1988). In other words, parties obtain their outside options forever following a deviation. The right-hand-side (RHS), π_t, denotes the gain from a one-time deviation in period t. The DICC captures the idea that parties will not breach the commitment so long as future relationship-specific gains are sufficiently high relative to opportunistic behavior.

A. Setup

The buyer (b) and the seller (s) potentially interact an indefinite number of periods t, $t = 1, 2, ...$, and share a common discount factor $\delta < 1$. In each period, the buyer demands q units of vegetables from the seller for which she can sell to a downstream buyer (e.g., a secondary wholesaler, restaurant, supermarket) at an exogenous price of p^D, net transportation costs. Given the stylized fact that there are on average 5 times more buyers than sellers on one single day, we let the seller bring to the market a large amount of vegetable to satisfy any q that buyer may ask for. For the seller, he faces a given marginal cost of buying from farmers at c.

[9] Alternatively, we can assume forming relationships saves some sort of cost, such as search or planning cost. The cost saving assumption would generate qualitatively similar results and predictions, but do not match empirical and field evidence as closely as the quantity assurance assumption.

Instead of forming direct relationships, both b and s could participate in the spot market, albeit anonymously. Participants have no memory of the history of transactions with each other. Since supply and demand are highly volatile, neither price nor quantity could be secured on the spot market.

A relational contract (RC) negotiated in period t is given by $C_t = \{q_t, p_t^{RC}\}_{t=1,2,...}^{\infty}$. The contract specifies quantities to be delivered and a unit price to be paid upon delivery. In reality, the delivery is typically arranged by a phone call or text message between b and s hours before the transaction takes place. All transactions feature on-site cash and good transfer. There is no risk in deferred payment or delivery. The division of surplus is realized through $p_t^{RC} - p_t$, and is essentially determined by bargaining between the buyer and the seller (Doornik, 2006). To simplify the analysis, I abstract from haggling and assume that the price quote is a take-it-or-leave-it offer as in Antras and Foley (2015). The assumption is made throughout the analysis and echos field evidence.

A relational contract has the same design as a formal contract but lack of enforcement exposes the contracting parties to opportunistic breach of one another. For the seller, the buyer could cancel her order or switch to another seller to purchase the desired amount. For the buyer, since p_t is not contractible, the seller has all the ex post bargaining power. In essence, this means the seller could expropriate the quasi-rent (Board, 2011). A relational contract must be self-enforcing to overcome these problems.

I now describe the DICC in detail. The RHS of DICC is relatively easy to construct. Under RC, the current period buyer return is $(p^D - p^{RC})q$, and seller return is $(p^{RC} - c)q$. Denote as p the spot market price. If RC is breached in period t, the buyer has to buy on the spot market, and face an expected rate of rationing (i.e., expected percentage of q not fulfilled), $\phi^b < 1$. The seller also has to sell on the spot market, and the expected percentage of seller supply of q not sold on the spot market equals $\phi^s < 1$. When RC is breached, the returns become $(p^D - p)(1 - \phi^b)q$ for b and $[p(1 - \phi^s) - c]q$ for s, respectively. In the baseline setup, we normalize the quantity traded, q to 1, which we make a choice variable later in the section. The return from defaulting is

$$(3) \qquad (p^D - p)(1 - \phi^b) - (p^D - p^{RC}) = (p^{RC} - p^D\phi^b) - p(1 - \phi^b)$$

for the buyer, and

$$(4) \qquad -p^{RC} + p(1 - \phi^s)$$

for the seller. The RHS expressions for buyer and seller add up to $-(p^D - p)\phi^b - p\phi^s$.

The left-hand-side (LHS) of DICC captures the expected difference between maintaining/continuing the RC and staying on the spot market from period $t+1$

and on. The latter is easy to get:

$$b : U^{b0}_{t+1} = (\overline{p^D} - \overline{p})(1 - \phi^b)\frac{\delta}{1-\delta} \tag{5}$$

$$s : U^{s0}_{t+1} = \overline{p}(1 - \phi^s)\frac{\delta}{1-\delta} - c\frac{\delta}{1-\delta} \tag{6}$$

where the upper bar indicates the expected price.

U^b_t and U^s_t are the discounted payoff stream expressed in per-period averages. We follow Macchiavello and Morjaria (2015) to define a variable μ_t as the expected probability that RC is not breached in any period after t, which is an increasing function of RC age and cumulative volume traded based on the Bayes' Theorem (which is further illustrated later).

$$\begin{aligned} U^b_{t+1} &= \sum_{\tau=1}^{\infty}(\overline{p^D} - p^{RC})\mu^{\tau}_t\delta^{\tau} \\ &+ \sum_{\tau=1}^{\infty}\mu_t^{\tau-1}(1-\mu_t)\delta^{\tau}[(\overline{p^D} - \overline{p})(1-\phi^b) + \sum_{T=1}^{\infty}(\overline{p^D} - \overline{p})(1-\phi^b)\delta^T] \\ &= (\overline{p^D} - p^{RC})\frac{\mu_t\delta}{1-\mu_t\delta} + (\overline{p^D} - \overline{p})(1-\phi^b)\frac{\delta}{1-\delta}\frac{1-\mu_t}{1-\mu_t\delta} \end{aligned} \tag{7}$$

We hence find:

$$\begin{aligned} \Delta U^b_{t+1} &= (\overline{p^D} - p^{RC})\frac{\mu_t\delta}{1-\mu_t\delta} - (\overline{p^D} - \overline{p})(1-\phi^b)\frac{\delta}{1-\delta}\frac{\mu_t(1-\delta)}{1-\mu_t\delta} \\ &= -[(p^{RC} - \overline{p}) - (\overline{p^D} - \overline{p})\phi^b]\frac{\mu_t\delta}{1-\mu_t\delta} \end{aligned} \tag{8}$$

Similarly, we find the LHS terms for the seller

$$\Delta U^s_{t+1} = [(p^{RC} - \overline{p}) + \overline{p}\phi^s]\frac{\mu_t\delta}{1-\mu_t\delta} \tag{9}$$

It is easy to see that both ΔU^b_{t+1} and ΔU^s_{t+1} increase in μ_t and δ. The sum of the two equals the net aggregate surplus of continuing the relationship:

$$\Delta S^s_{t+1} = \Delta U^b_{t+1} + \Delta U^s_{t+1} = [(\overline{p^D} - \overline{p})\phi^b + \overline{p}\phi^s]\frac{\mu_t\delta}{1-\mu_t\delta} \tag{10}$$

B. Optimal quantity traded

Alternatively, we normalize the total quantity of purchase for the buyer and let the buyer choose a portion $q \in [0, 1]$ traded under RC in any period t. The rest is fulfilled on the spot market. The buyer maximizes expected profits in t by optimally allocating procurement between RC and the spot market. Her objective function is:

$$max_{q_t} \pi_t^b = (\overline{p^D} - p^{RC})\mu_t q_t + (\overline{p^D} - \overline{p})(1-\mu_t)(1-\phi^b(q_t))q_t + (\overline{p^D} - \overline{p})(1-\phi^b)(1-q_t) \quad (11)$$

The first two terms capture the expected profits from RC. If the RC breaks down in period t, the portion unfulfilled would be an increasing, concave function of q_t because q_t comes to the spot market as a surprise. Without loss of generosity, let the portion be:[10]

$$\phi^b(q_t) = \phi q_t \quad (12)$$

For this portion only, the buyer faces $\phi^b(q_t) > \phi^b$ for any q_t. For the portion of $1 - q_t$ that is planned to be traded on the spot market, the expected portion unfulfilled is a given rate of ϕ^b because $1 - q_t$ does not come to the market as a surprise. The assumption that $\phi^b(q_t) > \phi^b$ for any q_t reflects the central tradeoff between trading on spot market and trading via RC — the cost of forming RC, as opposed to trading entirely on the spot market, is the increase in likelihood of being rationed when the contractual party defaults. When s defaults, b has to search on the spot market to fulfill the portion q_t with a higher probability of being rationed — $\phi^b(q_t) > \phi^b$.

The optimal amount to be traded under RC can be found using the F.O.C.:

$$\frac{\partial \pi_t^b}{\partial q_t} = (\overline{p^D} - p^{RC})\mu_t + (\overline{p^D} - \overline{p})(1-\mu_t)(1-\phi q_t) - (\overline{p^D} - \overline{p})(1-\mu_t)\phi q_t - (\overline{p^D} - \overline{p})(1-\phi^b) \quad (13)$$

which gives

$$q_t^* = \frac{(\overline{p^D} - \overline{p})\phi^b + (\overline{p} - p^{RC})\mu_t}{2(\overline{p^D} - \overline{p})(1-\mu_t)\phi} \quad (14)$$

Except for special cases, q_t^* is neither 1 nor 0, implying the coexistence of RC and spot market in equilibrium. Note that q_t is the base for expectation of future

[10] A linear functional form would give qualitatively same results. I use linear for now and can change it later.

volume traded in period t, which will not be adjusted in period $t+1$ onward in equation (7).

It is easy to show that:

$$\frac{\partial q_t^*}{\partial \mu_t} > 0 \quad \frac{\partial q_t^*}{\partial \phi^b} > 0 \quad \frac{\partial q_t^*}{\partial p^{RC}} < 0 \quad \frac{\partial q_t^*}{\partial \phi} < 0 \tag{15}$$

which are all intuitive.

The expected RC return functions, equations (8) and (9), are updated with $\phi^b(q_t) = \phi q_t$. Specifically, with q_t as a common multiplier for all terms in U^b_{t+1} and hence suppressed, the expected return to the buyer under RC is:

$$\begin{aligned} U^b_{t+1} &= \sum_{\tau=1}^{\infty} (\overline{p^D} - p^{RC}) \mu_t^\tau \delta^\tau \\ &+ \sum_{\tau=t}^{\infty} \mu_t^{\tau-1} (1-\mu_t) \delta^\tau [(\overline{p^D} - \overline{p})(1-\phi^b(q_t)) \sum_{T=1}^{\infty} (\overline{p^D} - \overline{p})(1-\phi^b)\delta^T] \end{aligned} \tag{16}$$

and equation (8) becomes

$$\Delta U^b_{t+1} = (\overline{p^D} - p^{RC}) \frac{\mu_t \delta}{1-\mu_t\delta} + (\overline{p^D} - \overline{p})(1-\phi^b(q_t)) \frac{(1-\mu_t)\delta}{1-\mu_t\delta} - (\overline{p^D} - \overline{p})(1-\phi^b) \frac{\delta}{1-\mu_t\delta} \tag{17}$$

With q_t as a common multiplier for all terms in ΔS_{t+1} and hence suppressed, the sum of LHS for buyer and seller DICC is.

$$\Delta S_{t+1} = (\overline{p^D} - \overline{p})[\phi^b(q_t)\mu_t - (\phi^b(q_t) - \phi^b)] \frac{\delta}{1-\mu_t\delta} + \overline{p}\phi^s \mu_t \frac{\delta}{1-\mu_t\delta} \tag{18}$$

Buyer's gain from default becomes

$$(p^D - p) q_t (1 - \phi^b(q_t)) - (p^D - p^{RC}) q_t \tag{19}$$

and seller's gain from default becomes

$$pq_t(1-\phi^s) - p^{RC}q_t \tag{20}$$

The sum of RHS of DICC becomes

$$-pq_t\phi^s - (p^D - p)q_t\phi^b(q_t) \tag{21}$$

which is always negative. The larger μ_t, the larger ΔS_{t+1}. Everything else the same, therefore, a relatively large q_t under RC can be sustained given a relatively large μ_t. When μ_t and ϕ^s are small, S_{t+1} is likely negative as long as $\overline{p^D} > \overline{p}$. Thus, S_{t+1} could be smaller than the sum of DICC RHS and make sustaining the RC suboptimal.

C. Testable Hypotheses

We now discuss how the model rationalizes the stylized facts shown in section II, and derive additional testable hypotheses based on the model's comparative statics.

Seller's premium. — The split of surplus between b and s is governed by the relative magnitude of ϕ^b and ϕ^s. To see why, consider a shock that causes the spot market price p to change by Δp, the RHS for buyer DICC changes by $\Delta p(1-\phi^b)$ and that for seller changes by $\Delta p(1-\phi^s)$. The magnitude of change is greater for the seller as long as $\phi^b > \phi^s$, which is a stylized fact of the market studied. Thus, the seller is more likely to find the return to RC below the gain from default.

To sustain the relationship, p^{RC} needs to be set higher than $\overline{p}$, which explains the fact that on average, sellers are charging a price premium from their relational buyers.

price stickiness. — Although not a direct prediction, price stickiness in relationships is an implicit indication of the model. When spot market p rises sharply, for instance, the RHS of seller DICC rises accordingly and creates strong incentive for the seller to default. Upon this event, the two parties could very well use a higher one-time p^{RC} to bring the RHS of seller DICC lower than ΔU^s_{t+1} so that the RC is maintained. Of course, higher one-time p^{RC} should not be so that the RHS of buyer DICC exceeds ΔU^b_{t+1}. That means, the increase in p^{RC} is smaller in magnitude than the increase in p. As a result, p^{RC} is stickier than p, a stylized fact shown previously. An extreme market price shock, however, could still break an RC even allowing for flexibility in p^{RC} in a particular period.

Tests. — I list here two major testable predictions from the model's comparative statics. Detailed proof can be found in the online Appendix.

- **Test 1**: *RC premium is suppressed when there is a negative shock (market price increase), and enlarged when there is a positive shock (market price drop), entitling RC a price insuring function.*
- **Test 2**: *The likelihood of being rationed is smaller for buyers in relationships, and decreases as the relationship ages and accumulates volume traded. The RC purchase share of a buyer increases in the age of RC.*

IV. Empirical Results

This section tests these hypotheses with the data and presents the results. I provide a quantification of relationship's value at the end and conduct additional tests regarding strategic defaults.

A. Test I: Relationships Provide Price Insurance

To test if (forming a) relationship can mitigate the negative impact of high supply volatility, I first identify supply shocks. Supply shocks are observed as unanticipated increase/decrease in volume of vegetables delivered to the market. The causes of supply shocks are mixed. For example, a negative supply shock could be due to extreme weather in production regions, or high-way lock-downs, or non-presence of several big sellers. Thus, it is hard to employ a universal exogenous identifier. I resort to using the total trading volume of the day as a proxy. As mentioned earlier, market for CC (and most other vegetables) clears on most days, thus fluctuation in total trading volume should be largely attributed to supply side factors. In addition, there is no significant seasonality in demand for CC due to dietary habits or holiday traditions. We could thus safely attribute the fluctuation in trading volume to supply side factors, a key assumption in the empirical strategy.

Specifically, the supply shock dummies are defined based on two-week rolling average of daily total volume. Days when supply is one standard deviation below the average are denoted as days with low supply (negative shock), and one standard deviation above the average as days with high supply (positive shock). The main identifying variation that I leverage comes from large and sudden jumps in market supply levels relative to smooth seasonal trends. Figure A2 in the Appendix shows the distribution of positive and negative supply shocks, which is largely symmetric. Column (1) and (2) in Table A3 shows that positive shocks cause prices to drop, while negative shocks cause prices to increase at the market level.

I use two approaches to test the hypothesis. The first test is rather simple. I interact the relationship dummy with the supply shock dummies to baseline regression equation 1 and estimate the specification:

$$P_{ij,t} = \alpha_1\, R_{ij,t} + \alpha_2\, R_{ij,t} \times PS_t + \alpha_3\, R_{ij,t} \times NS_t + \beta Z_{ij,t} + \theta_i + \epsilon_{ij,t} \quad (22)$$

If price response in relational transactions is different under exogenous shocks, reflecting a strategic response of the trading parties to the tightening or slacking of the self-enforcement constraint, then we would know there is value embedded in relationships in times of shocks. Column (1) and (2) in Table 6 presents the results. Column (1) includes seller-day fixed effects, while column (2) imposes seller, year, and month fixed effects. Both regressions controls for time (hour fixed effects) and share of sales/purchase.

The second test involves construction of 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 average market price $\bar{P}_t - \bar{P}_{t-1}$.

$$vol_{ij,t} = \frac{P_{ij,t} - P_{ij,t-1}}{\bar{P}_t - \bar{P}_{t-1}} \tag{23}$$

The ratio reflects the volatility in pairwise trade relative to the market average trend. If the ratio of pair $i - j$ equals one on day t, the pair is experiencing same volatility as the market. A ratio smaller than one indicates that the pair is experiencing a smaller price change, thus less volatility. To construct the ratio, I first identify pairwise consecutive transactions from the data, i.e., find pairs who have consecutive transactions for at least two days and calculate the change in their transactional price from $t-1$ to t. To ensure that the comparison is valid, we need a substantial amount of relational transactions. In the sub-sample, 14,388 out of 34,248 (about 40%) transactions are relational.

The major RHS variables in regression 22 are kept, while seller-day fixed effects and controls for buyer and seller's shares are removed. Based on hypothesis 2, one would expect the sign of $R_{ij,t}$ to be negative, which would prove that relationships serves as a cushion against price fluctuation and provides price insurance for the trading parties. Further, the signs of the two interaction terms should also be negative. The benefits of relational contracting is enlarged under supply shocks. Column (3) and (4) in Table 6 presents the results. Year, month and hour fixed effects are added in column (3). All coefficients of interest have the expected signs and are significant.

B. Test 2: Relationships Provide Supply Assurance

In market where trade is frequent and where sellers cannot hold inventories, the essential risk for a buyer is not that of paying too higher a price but rather of not being served at all (Weisbuch, Kirman and Herreiner, 2000). If not being served at all sounds too extreme, at least they constantly face the risk of being rationed — not getting the amount they want due to supply scarcity. Markets for perishable agricultural products in developing countries provide perhaps the best illustration. In these markets, supply is sensitive to weather and transportation conditions, making it highly volatile. The composition of producers — a large proportion being smallholder farmers — also adds uncertainty to the total volume

Table 4—Relationships provide price insurance (Test 1)

Dependent variable:	transaction price		volatility ratio	
Sample	All transactions	All transactions	Consecutive transactions	Consecutive transactions
	(1)	(2)	(3)	(4)
Relationship	.063***	.060***	-.018	-.022
	(.002)	(.002)	(.013)	(.015)
Relationship × Positive shock	.026***	.025***	-.082***	-.073***
	(.004)	(.004)	(.025)	(.025)
Relationship × Negative shock	-.002*	-.077***	-.078**	.-.064**
	(001)	(.005)	(.030)	(.030)
Total trading volume of the day		-.000***		
		(.000)		
Yesterday's average market price		.813***		
		(.002)		
Seller fixed effects	Y	Y	N	N
Trading day fixed effects	Y	N	N	N
Year fixed effects	N	Y	Y	N
Month fixed effects	N	Y	Y	N
Hour fixed effects	Y	Y	Y	N
Adjusted R^2	.693	.635	.010	.008
Observations	178,856	178,856	39,914	39,914

Note: Buyer's share refers to the share of buyer i's purchase in seller j's total sales on day t; seller's share refers to the share of seller j's sales in buyer i's total purchase on day t. (Might omit the shares in the table b/c if there is no specific theoretical hypothesis fored about them.) The volatility ratio is supposed to be non-negative. Issues arise when the numerator is zero and when either the numerator or the denominator is very small so that we get a very large ratio. Detailed treatment of outliers and the distribution of the ratio are given in the Appendix.

that arrives at the market on each trading day. During the field interviews, some buyers claimed that they are rationed occasionally and experiencing rationing was costly — they usually have downstream obligations to fulfill, indicating the value of insurance against rationing.

The empirical literature on relational contracting have showed that buyers are able to gain supply assurance through repeated trade relationships. Macchiavello and Morjaria (2015) show that in Kenyan rose exporting, the length of relationship relates to the provision of supply assurance through prioritization. They use a model to predict and prove empirically that the reliability of rose delivery during the violence is an inverted-U shaped function of the age of the relationship. The reliability of delivery is measured by a ratio between actual shipments volumes during the week of the violence divided by the average volume shipped in the relationship during the control period. The test is taken within the sample of relationships. They did not compare the difference in delivery reliability between relational- and non-relational trade. Ghani and Reed (2019) show that in Sierra Leone's ice industry, ice retailers prioritize deliveries to loyal fishing firms (buyers) when supply from the monopolistic manufacturer is scarce. In other words, fishermen perceived as loyal receive priority deliveries on days when retailers experience more difficulty procuring ice from M1. When supply is scarce and M1 rationed supply to the fishermen at wharves, this often resulted in M1 making some ice truck deliveries on time and other late, providing retailers with an opportunity to provide supply assurance to selected customers. Ghani and Reed (2019) are able to identify late deliveries in the data. They use a linear probability model to test if fishermen considered loyal are less likely to receive late deliveries on days in which supply is scarce.

In the well-functioning wholesale market, is the provision of supply assurance still a motivation for relationship establishment? In this context, timely delivery no longer indicate supply assurance — delivery is always "guaranteed" since we only observed transactions that happened. In addition, transaction time does not always indicate the order of serving, and even if it does, we cannot know if a transaction is delayed to the extent that it affected the buyer's downstream business. In fact, it is learned from the field interviews that relational buyers could make an order anytime through text messages, even before the market opens, but the real transaction is recorded when the buyer dispatch an employee to get the product and make the payment.

ZISF MODEL. — What can be examined is the outcome — whether and by how much each buyer is rationed at each visit. In other words, whether the buyer was able to purchase the amount she wanted and if not, how much less. Being rationed less frequently and less severely means the buyer receives a higher degree of supply assurance. I use the Zero Inefficiency Stochastic Frontier (ZISF) model to estimate the frequency and magnitude of rationing experienced by each individual buyer. I then test if rationing is systematically related to relational activities of the buyer — whether the buyer has a relationship, the number of relationships she has, and the percentage of her purchase that is made through relational purchase.

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. Stochastic frontier analysis assumes that each firm potentially produces less than it might due to a degree of inefficiency. When adapted to the estimation of buyers' demand function, the degree of rationing corresponds to the degree of inefficiency in the production SFM.

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

$$Q^i_t = p^{i^{\gamma}}_t exp(\alpha^i + Z^i_t\beta + \upsilon^i_t) \tag{24}$$

where p^i_t is the price buyer i faces on day t[11], υ^i_t is i.i.d. $N(0, \sigma^2_\upsilon)$ and captures the effects of unobservable characteristics and measurement error. 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, on the other hand, is

$$q^i_t = \theta^i_t p^{i^{\gamma}}_t exp(\alpha^i + Z^i_t\beta + \upsilon^i_t) \tag{25}$$

where θ^i_t is a random variable between 0 and 1. A logarithmic transformation of (6.5) yields a linear equation,

$$\ln q^i_t = \alpha^i + Z^i_t\beta + \gamma p^i_t + \upsilon^i_t + \ln\theta^i_t \tag{26}$$

Let $u^i_t = -\ln(\theta^i_t)$, we have

$$\ln q^i_t = \alpha^i + Z^i_t\beta + \gamma p^i_t + \upsilon^i_t - u^i_t \tag{27}$$

It is nevertheless not plausible to assume that buyers are rationed on each single visit. In fact, they should be able to purchase according to their demand on a good number of days. The obvious caveat of using the traditional SFM is that it assumes each observation is inside the efficiency frontier, i.e., there is some degree of inefficiency (rationing) associated with each observation, thus not able to accommodate the case when some observations are fully efficient (no ration). Introduced by Kumbhakar, Parmeter and Tsionas (2013) Kumbhakar, Parmeter and Tsionas (2013), the Zero Inefficiency Stochastic Frontier model is a modification of the standard SFM that allows both fully efficient and inefficient observations in the sample. Specifically, ZISF allows zero inefficiency by assuming the inefficiency term, $u^i_t = 0$ for some t and $u^i_t > 0$ for others.

Suppose buyer i is rationed with probability ρ^i and not rationed with probability $1-\rho^i$. The composed error term is $\upsilon^i_t - u^i_t(1-1\{u^i_t = 0\})$ where $1\{u^i_t = 0\} = \rho^i$. The idiosyncratic component, υ^i_t, is assumed to be independently $N(0, \sigma_{\upsilon^i})$ distributed over the observation-days and the inefficiency term, u^i_t, can be specified as independently half-normally $N^+(0, \sigma^2_{u^i})$ distributed. The only additional parameter in the ZISF model compared to the standard SF model is ρ^i. The statistical identification of this parameter requires non-zero observations in non-rationed

[11]For buyers who paid multiple prices on a day, p^i_t is the lowest price i paid. The logic is that if i is not rationed, she should be able to purchase $q^i(p^i_t)$ at the lowest price p^i_t.

days, which is a valid assumption in our context.

For each individual buyer i, I perform the estimation on i's time series of purchases q_t^i, $t = 1, 2, ..., T^i$ where T^i is different across buyers. I restrict the estimation to the sub-sample of buyers who have a $T^i > 200$, with a total of 241 buyers.[12] The estimation generates observation(day)-specific posterior probabilities of being rationed for each t, $1 - \breve{\rho}_t^i$:

$$1 - \breve{\rho}_t^i = 1 - \frac{(\hat{\rho}/\hat{\sigma}_v)\phi(\hat{\varepsilon}_t/\hat{\sigma}_v)}{(\hat{\rho}/\hat{\sigma}_v)\phi(\hat{\varepsilon}_t/\hat{\sigma}_v) + ((1-\hat{\rho}))\frac{2}{\hat{\sigma}}\phi(\hat{\varepsilon}_t/\hat{\sigma})\Phi(-\hat{\varepsilon}_t/\hat{\sigma}_0)} \tag{28}$$

where $\sigma = \sigma_v^2 + \sigma_u^2$, $\sigma_0 = \sigma_u/\sigma_v\sigma$. For brevity, all subscription i on the RHS are omitted. I follow one of Kumbhakar, Parmeter and Tsionas (2013)'s approaches and censor the posterior estimates $\breve{\rho}_t^i$ as follows:

- $\breve{\rho}_t^i \geq 0.95$: i is not rationed on t
- $\breve{\rho}_t^i < 0.95$: i is rationed on t with a JLMS inefficiency score

For those days with a posterior probability of full efficiency greater than 0.95, I assign an inefficiency/rationing level of zero, whereas for those days that have a posterior probability less than 0.95 I assign to them their JLMS inefficiency score (the conditional mean estimator for u for each observation) constructed using the ZISF ML estimates with $\rho^i = 0$:

$$\hat{u}_t^i = (1-\hat{\rho})\frac{\hat{\sigma}_u^2}{\hat{\sigma}_u^2 + \hat{\sigma}_v^2}[\hat{\sigma_0}\frac{\phi(\hat{\varepsilon}_t/\hat{\sigma}_0)}{\phi(-\hat{\varepsilon}_t/\hat{\sigma}_0)} - \hat{\varepsilon}_t] \tag{29}$$

Again, the subscription i is omitted for brevity. The ratio of rationing is thus

$$\hat{R}_t^i = 1 - \theta_t^i = e^{u_t^i} - 1 \tag{30}$$

The estimation is performed for each individual buyer's time series of purchases. I need advice on how to account for autocorrelation between purchases (for example, block bootstrapping). The gaps between purchases are unbalanced. Yet a majority of the purchases are consecutive (gap = 1). The table below gives a summary.

ALTERNATIVE WAYS OF MEASURING SUPPLY ASSURANCE. — An alternative measure of supply assurance is a ratio of reliability analogous to the one in Macchiavello

[12]In KPT, the statistical reliability of the model is validated when $n > 200$, which is when the performance of the PRL statistic appears to follow closely the asymptotic distribution.

TABLE 5—SUMMARY STATISTICS — GAP BETWEEN PURCHASES

	min	10%	median	90%	max
gap(min)	1	1	1	1	2
gap(p10)	1	1	1	2	2
gap(median)	1	1	1	3	3
gap(p90)	1	2	4	8	13
gap(max)	50	95	207	280	613
number of visits	200	213	298	460	798

and Morjaria (2015) (equation (13)). It is the ratio between actual volume of purchase on day t divided by the average volume purchased in the control period, which I define as the two weeks before and the two weeks after t excluding shock days:

$$\hat{R}_t^i = \frac{q_t^i}{\bar{q}_t^i} \tag{31}$$

where q_t^i is the volume of purchase of buyer i on day t, and $\bar{q}_t^i$ is the average volume of purchase in the control period.[13]

HYPOTHESIS TESTING. — Macchiavello and Morjaria (2015) and Ghani and Reed (2019) employ the same logic in testing supply assurance: they first show that delivery is less reliable under violence/scarce supply, then show that under these circumstances, relationships increase the reliability of (on-time) delivery. Similarly, I show that rationing is more likely and more severe (reliability is reduced) under negative supply shocks, and then show that relationships reduce the likelihood/magnitude of rationing (increase reliability). Formally, I estimate the following model:

$$\begin{aligned}\hat{R}_t^i =& \beta_1 NS_t + \beta_2 RB_{y(t)}^i \times NS_t + \beta_3 RB_{y(t)}^i \\ &+ \gamma X_t^i + \tau_{m(t)} + \tau_{y(t)} + \epsilon_t^i\end{aligned} \tag{32}$$

in which $\hat{R}_t^i$ stands for either the measure of rationing or the measure of reliability. X_t^i is a vector of buyer controls, which are average price and volumes during the control period. The specification includes year fixed effects, $\tau_{y(t)}$, and month fixed effects, $\tau_{m(t)}$. Note that the sign of β should be different when we employ different measures — a negative and significant β would confirm that negative

[13]In the estimation, I trim the data to exclude observations that has no purchase in the control period.

supply shocks reduce reliability, while a positive and significant β would confirm that negative shocks increase the likelihood and magnitude of rationing.

$RB^i_{y(t)}$ is an indicator variable that equals one if i is a relational buyer — buyer with relationship(s) in that year. The interaction term tests if being a relational buyer would increase supply assurance, which is our major interest. Using variation from buyers who purchase from more than 1 seller, I also estimate the direct effect of relationship on rationing/reliability through β_3.

Restricting the sample to relational buyers only, the dummy variable RB can be replaced by the intensity of i's relational activity, proxied by the percentage of purchase made from relational sellers and the number of relationships i possess simultaneously.[14] When using the reliability ratio as the dependent variable, I include an additional control vector X^i_t, which consists of average purchase price and volumes during the control period.

Table 6 reports result of Test 2. By virtue of having a relationship (relational seller), the buyer experience a lowe likelihood of being rationed. The supply securing effect of an RC appears more significant when there is a negative supply shock. In addition, the more a buyer purchase through RC, the more security is locked. The reliability ratio approach reveals qualitatively same results.

V. Concluding Remarks

Relational contracts use repeated trade to support price insurance and supply assurance when market is incapable in such provision. While previous literature has documented the value of direct relationships when spot market exchange is not accessible, I present a case study which exemplifies the formation and value of RC when a market is well-functioning and no salient frictions exist.

With micro-level evidence extracted from administrative transaction-level data, this study reveals the role of existing relations among vegetable traders in shaping the transmission of inter-temporal price risk, and in improving security in supply. The risk faced by each individual are mitigated by a pattern of bilateral agreements, which deal with uncertainty through a system of reciprocation over time. Thus, well-functioning markets are not necessarily the enemy of relational contracting. The findings add a piece to the puzzle of the emergence of RC in two-tier markets with no evident market frictions. The value of relational contracting is high when supply uncertainty and price volatility is high, which are pervasive features of many markets, especially markets for agricultural products. Such knowledge can be beneficial for the design of market institutions, particularly in a development context.

[14] If the intensity variable is used in the whole-sample regression, it would be a censored variable which equals zero when the buyer is not a relational buyer. Alternatively, we can use the percentage of purchase from each buyer's primary seller, i.e., the seller from whom i made the most purchase from, be him i's relational seller or not, as the intensity measure.

Table 6—Relationships provide supply assurance (Test 2)

Dependent variable:	rationing likelihood		reliability ratio	
Sample	All buyers	Relational buyers	All buyers	Relational buyers
	(1)	(2)	(3)	(4)
RB	-.181***			
	(.037)			
RB × Negative shock	-.002*	-.077***	.020***	
	(001)	(.005)	(.009)	
Fraction of RC purchase		-.058***		.130***
		(.021)		(.011)
Negative shock			-.027***	-.015***
			(.006)	(.004)
Year fixed effects	Y	Y	Y	Y
Month fixed effects	Y	Y	Y	Y
Adjusted R^2	.693	.635	.010	.065
Observations	363	125	73,365	73,365

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