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The Value of Relationships: Evidence from a Supply Shock to Kenyan Rose Exports[†]

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This paper provides evidence on the importance of reputation in the context of the Kenyan rose export sector. A model of reputation and relational contracting is developed and tested. A seller's reputation is defined by buyer's beliefs about seller's reliability. We show that (*i*) *due to lack of enforcement, the volume of trade is constrained by the value of the relationship;* (*ii*) *the value of the relationship increases with the age of the relationship; and* (*iii*) *during an exogenous negative supply shock deliveries are an inverted-U shaped function of relationship's age. Models exclusively focusing on enforcement or insurance considerations cannot account for the evidence.* (*JEL* D86, F14, L14, O13, O19, Q17)

Imperfect contract enforcement is a pervasive feature of real-life commercial transactions. In the absence of formal contract enforcement, trading parties rely on informal mechanisms to guarantee contractual performance (e.g., Johnson, McMillan, and Woodruff 2002; Greif 2005; Fafchamps 2010). Among those mechanisms, long-term relationships based on trust or reputation are perhaps the most widely studied and have received substantial theoretical attention. The theoretical literature has developed a variety of models that capture salient features of real-life relationships, e.g., enforcement problems (e.g., MacLeod and Malcomson 1989; Baker, Gibbons, and Murphy 1994; Baker, Gibbons, and Murphy 2002; Levin

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2003), insurance considerations (e.g., Thomas and Worrall 1988), or uncertainty over parties commitment to the relationship (e.g., Ghosh and Ray 1996; Watson 1999; Halac 2012). While these different models share the common insight that future rents are necessary to deter short-term opportunism, they also differ in important aspects. Empirical evidence on informal relationships between firms, therefore, has the potential to identify which frictions are most salient in a particular context. In turn, such knowledge can be beneficial for policy, particularly in a development context. Empirical progress in the area, however, has been limited by the paucity of data on transactions between firms in environments with limited or no formal contract enforcement and challenges in measuring future rents and beliefs.

This paper provides evidence on the importance of reputation, intended as beliefs buyers hold about seller's reliability, in the context of the Kenyan rose export sector. A survey we conducted among exporters in Kenya reveals that relationships with foreign buyers are not governed by written contracts enforceable in courts. The perishable nature of roses makes it impractical to write and enforce contracts on supplier's reliability. Upon receiving the roses, the buyer could refuse payment and claim that the roses did not arrive in the appropriate condition while the seller could always claim otherwise. The resulting contractual imperfections, exacerbated by the international nature of the transaction, imply that firms rely on repeated transactions to assure contractual performance.

The analysis takes advantage of three features of this setting. First, unlike domestic sales, all export sales are administratively recorded by customs. We use four years of transaction-level data of all exports of roses from Kenya, including the names of domestic sellers and foreign buyers, as well as information on units traded, prices, and transaction date. Second, in the flower industry, direct supply relationships coexist alongside a well-functioning spot market, the Dutch auctions.[1] If roses transacted in the relationships can be traded on the auctions, incentive compatibility considerations imply that the spot market price can be used to compute a lower bound to the future value of the relationship. Third, a negative supply shock provides a unique opportunity to test the predictions of the reputation model and distinguish it from alternative models. Following heavily contested presidential elections in Kenya at the end of December 2007, several, but not all, regions of the country plunged into intense episodes of ethnic violence in January 2008. Flower exporters located in some regions suddenly found themselves lacking significant proportions of their labor force and suffered a dramatic drop in exports. We examine how exporters reacted to the violence and which relationships they prioritized.

We first present a model of the relationship between a rose producer (seller) and a foreign buyer (buyer). The setup of the model matches qualitative features of the market under consideration. The model is analyzed under three scenarios: (i) the benchmark case with no contract enforcement; (ii) an extension with uncertainty over the seller's type; and, finally, (iii) an extension to examine the seller's reaction to the violence. The three different scenarios are used to explicitly derive three

[1] The "Dutch", or "clock", auction is named after the flower auctions in the Netherlands. In a Dutch auction the auctioneer begins with a high asking price which is lowered until some participant is willing to accept, and pay, the auctioneer's price. This type of auction is convenient when it is important to auction goods timely, since a sale never requires more than one bid.

empirical tests. The version of the model with no contract enforcement, developed along the lines of the relational contracts literature, is analyzed first. The incentive compatibility constraints of the model clarify how information on quantities transacted, prices in the relationships, and auction prices, which are all observable in the data, can be used to compute lower bounds to the value of the relationship for the buyer and the seller. The model also yields a simple test to establish whether the volume of trade in the relationship is limited by lack of contractual enforcement. The model is then extended to consider uncertainty over the seller's type and to examine how reputational forces influence the seller's reaction to the negative shock induced by the violence. Consistent with the interviews in the field, we model the violence as an unanticipated and observable shock that makes it impossible to deliver roses unless the seller undertakes additional costly and unobservable effort (e.g., hire extra security, set up camps to host workers menaced by the violence). The model predicts an inverted-U shaped relationship between deliveries at the time of the violence and age of the relationship. Over time, the seller establishes a reputation for reliability. The relationship becomes more valuable and incentives to deliver during the violence to protect the valuable reputation increase with the age of the relationship. In sufficiently old relationships, however, a seller's reliability has been proven and deliveries at the time of the violence do not convey further information about future reliability.

When this is the case, incentives to protect the reputation and deliver during the violence vanish. We then test the predictions of the model. Measures of the value of the future rents in the relationship for the buyers and the sellers are computed. First, we find evidence consistent with incentive considerations limiting the volume of trade. Second, the estimated relationship values positively correlate with the age and past amount of trade in the relationship. The results, which hold controlling for relationship (which include seller, buyer, and cohort), time, and selection effects, are inconsistent with the pure limited enforcement version of the model but support the version with uncertainty over seller's type. At the time of the violence, exporters located in the region directly affected by the violence could not satisfy commitments with all buyers. The violence was a large shock and exporters had to chose which buyers to prioritize. We document an inverted-U shaped relationship between deliveries at the time of the violence and age of the relationship. We also provide direct evidence that firms located in the conflict region exerted costly effort to protect their relationships with foreign buyers. The evidence is consistent with the reputation model and is not consistent with other models, e.g., those that exclusively focus on enforcement or insurance considerations. We discuss the policy implications of these findings, particularly from the point of view of export promotion in developing countries, in the concluding section.

The findings and methodology of the paper contribute to the empirical literature on relationships between firms. McMillan and Woodruff (1999) and Banerjee and Duflo (2000) are closely related contributions that share with the current paper a developing country setting.[2] In an environment characterized by the absence of

[2] Banerjee and Munshi (2004); Andrabi, Ghatak, and Khwaja (2006); and Munshi (2011) provide interesting studies of contractual relationships in a development context, but with a rather different focus. For example, Munshi (2011) and Banerjee and Munshi (2004) provide evidence on the trade enhancing role of long-term relationships based on community ties. Andrabi, Ghatak, and Khwaja (2006) provide evidence of how flexible specialization attenuates hold-up problems. Hjort (2014) studies how ethnic divisions impact productivity using data from a

formal contract enforcement, McMillan and Woodruff (1999) find evidence consistent with long-term informal relationships facilitating trade credit. Banerjee and Duflo (2000) infer the importance of reputation by showing that a firm's age strongly correlates with contractual forms in the Indian software industry. Both McMillan and Woodruff (1999) and Banerjee and Duflo (2000) rely on cross-sectional survey evidence and cannot control for unobserved firm, or client, heterogeneity. In contrast, we exploit an exogenous supply shock and rely on within buyer-seller relationships evidence to prove the existence, study the source, and quantify the importance of the future rents necessary to enforce the implicit contract. Antras and Foley (forthcoming) and Macchiavello (2010) are two closely related studies in an export context. Antras and Foley (forthcoming) study the use of prepayment to attenuate the risk of default by the importer. Using data from a US based exporter of frozen and refrigerated food products they find that prepayment is more common at the beginning of a relationship and with importers located in countries with a weaker institutional environment. Macchiavello (2010), instead, focuses on the implications of learning about new suppliers in the context of Chilean wine exports. In the context of domestic markets, particularly for credit and agricultural products, Fafchamps (2000, 2004, 2010) has documented the importance of informal relationships between firms in Africa and elsewhere.[3]

The rest of the paper is organized as follows. Section I describes the industry, its contractual practices, and the ethnic violence. Section II introduces the model and derives testable predictions. Section III presents the empirical results. Section IV provides a discussion of the findings. Section V offers some concluding remarks and policy implications. Proofs, additional results, and further information on the data are available in the online Appendices.

I. Background

This section provides background information on the industry, its contractual practices, and the ethnic violence. The section relies on information collected through a representative survey of the Kenyan flower industry conducted by the authors through face-to-face interviews in the summer of 2008.

A. *The Kenyan Flower Industry*

Over the last decade, Kenya has become one of the largest exporters of flowers in the world. The flower industry, one of the largest foreign-currency earners for the Kenyan economy, counts around 100 established exporters located at various clusters in the country. Roses, the focus of this study, account for about 80 percent of exports of cut flowers from Kenya. Roses are fragile and perishable. To ensure

Kenyan flower plant. The literature on tied labor in rural contexts has studied the connections existing between spot markets and informal relationships (see, e.g., Bardhan 1983 and Mukherjee and Ray 1995).

[3] Alongside a larger literature that studies formal contracts between firms (see Lafontaine and Slade 2012 for a survey), some studies have focused on the relationship between informal enforcement mechanisms and formal contract choice (see, e.g., Corts and Singh 2004; Kalnins and Mayer 2004; Lyons 2002; Gil and Marion 2013). With the exception of Gil and Marion (2013), these papers also rely on cross-sectional data and proxy the rents available in the relationship with product, firm, or market characteristics that might affect contractual outcomes in other ways.

the supply of high-quality roses to distant markets, coordination along the supply chain is crucial. Roses are hand-picked in the field, kept in cool storage rooms at a constant temperature for grading, then packed, transported to Nairobi's international airport in refrigerated trucks owned by firms, inspected, and sent to overseas markets. The industry is labor intensive and employs mostly low educated women in rural areas. Workers receive training in harvesting, handling, grading, packing and acquire skills which are difficult to replace in the short-run. Because of both demand (e.g., particular events in the year such as Valentine's Day and Mother's Day) and supply factors (it is costly to produce roses in Europe during winter), floriculture is a seasonal business. The business season begins in mid-August.

B. *Contractual Practices*

Roses are exported in two ways: they can be sold in the Netherlands at the Dutch auctions or can be sold to direct buyers. Direct buyers are located in the Netherlands and elsewhere (including Western Europe, Russia, the United States, Japan, and the Middle East). The two marketing channels share the same logistic operations associated with exports, but differ with respect to their contractual structure. The Dutch auctions are close to the idealized Walrasian market described in textbooks. There are no contractual obligations to deliver particular volumes or qualities of flowers at any particular date. Upon arrival in the Netherlands, a clearing agent transports the flowers to the auctions where they are inspected, graded, and finally put on the auction clock. Buyers bid for the roses accordingly to the protocol of a standard descending price Dutch auction. The corresponding payment is immediately transferred from the buyer's account to the auction houses and then to the exporter, after deduction of a commission for the auctions and the clearing agent. Apart from consolidating demand and supply of roses in the market, the Dutch auctions act as a platform and provide a mechanism to enforce contracts between buyers and sellers located in different countries. The auctions certify the quality of the roses sold and enforce payments from buyers to sellers. It is common practice in the industry to keep open accounts at the auction houses even for those firms that sell their production almost exclusively through direct relationships. The costs of maintaining an account are small, while the option value can be substantial.

Formal contract enforcement, in contrast, is missing in the direct relationships between the flower exporter and the foreign buyer, typically a wholesaler. The export nature of the transaction and the high perishability of roses makes it impossible to write and enforce contracts on supplier's reliability. Upon receiving the roses, the buyer could refuse payment and claim that the roses sent were not of the appropriate variety and/or did not arrive in good condition. The seller could always claim otherwise. Accordingly, exporters do not write complete contracts with foreign buyers.[4]

Exporters and foreign buyers negotiate a marketing plan at the beginning of the season. With respect to volumes, the parties typically agree on some minimum

[4] Among the surveyed 74 producers, only 32 had a written contract with their main buyer. When a contract is written, it is highly incomplete. Among the 32 firms with a written contract, less than a third had any written provision on the volumes, quality, and schedule at which flowers have to be delivered. Written contracts often include clauses for automatic renewal. A handful of firms report to have had a written contract only in the first year of their relationship with a particular buyer.

volume of orders year round to guarantee the seller a certain level of sales. Parties might, however, agree to allow for a relatively large percentage (e.g., 20 percent) of orders to be managed "ad hoc." With respect to prices, most firms negotiate constant prices with their main buyer throughout the year but some have prices changing twice a year, possibly through a catalogue or price list. Prices are not indexed on quality nor on prices prevailing at the Dutch auctions.

Contracts do not specify exclusivity clauses. In particular, contracts do not require firms to sell all, or even a particular share, of their production to a buyer or to not sell on the spot market. In principle, it would seem possible to write enforceable contracts that prevent firms from side-selling roses at the auctions. The ability to sell on the spot market, however, gives producers flexibility to sell excess production as well as protection against buyers defaults and opportunism. Such contractual provisions might not be desirable.

This paper takes the existence of direct relationships as given and does not explain why relationships coexist along-side a spot-market.[5] Beside lower freight and time costs, a well-functioning relationship provides buyers and sellers with stability. Buyers' commitment to purchase pre-specified quantities of roses throughout the season allows sellers to better plan production. Buyers value reliability in supply of roses often sourced from different regions to be combined into bouquets. Parties trade off these benefits with the costs of managing and nurturing direct relationships in an environment lacking contract enforcement.

C. *Electoral Violence*

An intense episode of ethnic violence affected several parts of Kenya following contested presidential elections at the end of December 2007. The ethnic violence had two major spikes lasting for a few days at the beginning and at the end of January 2008. The regions in which rose producers are clustered were not all equally affected. Only firms located in the Rift Valley and in the Western Provinces were directly affected by the violence (see online Appendix C, Figure A1).[6] The main consequence of the violence was that firms located in the regions affected by the violence found themselves lacking a significant number of their workers. Among the 74 firms surveyed, 42 were located in regions that were directly affected by the violence. Online Appendix D, Table A1 shows that while firms located in regions not affected by the violence did not report any significant absence among workers (1 percent, on average), firms located in regions affected by the violence reported an average of 50 percent of their labor force missing during the period of the violence. Furthermore, firms were unable to completely replace workers. On average, firms in areas affected by the violence replaced around 5 percent of their missing workers and more than half of the firms replaced none. Many firms paid higher overtime wages to the remaining workers in order to minimize disruption in production.

[5] Similar two-tier market structures have been documented in several markets in developing countries (see Fafchamps 2010 for a review). The coexistence of direct relationships alongside spot markets is also observed in several other contexts, such as perishable agricultural commodities, advertising, and diamonds. We are grateful to Jon Levin for pointing this out to us.

[6] The classification of affected and unaffected regions is strongly supported by the survey conducted in the summer following the crisis and is not controversial. See online Appendix A for details.

TABLE 1—DESCRIPTIVE STATISTICS, DIRECT RELATIONSHIPS

Variable	Observations	Mean	SD	Min	Max
Panel A. Relationship characteristics					
Number of transactions	189	60.52	35.70	20.00	140
Number of stems per week (in 1000s)	189	100.24	161.85	0.81	926.49
Average FOB price (Euro cents per stem)	189	11.37	8.37	1.14	58.46
Age (in days)	189	830.27	469.54	24.50	1286
Number of previous transactions	189	309.88	304.51	12.00	1204
Left censored (Yes = 1, No = 0)	189	0.40	0.49	0	1
Panel B. Number of relationships per buyer and seller					
Number of relationships per seller	56	3.38	2.88	1	14
Number of relationships per buyer	71	2.66	2.83	1	14
Panel C. Estimated relationship values (*season before the violence*)					
Estimated S (/ average weekly revenues)	157	3.84	3.65	0.75	30.72
Estimated U (/ average weekly revenues)	157	2.70	1.77	0.77	10.64
Estimated V (/ average weekly revenues)	157	1.61	3.28	0.00	25.50

Notes: The sample is given by all relationships that had at least 20 transactions in the 20 weeks immediately before the violence. Left censored refers to relationships that were already active before August 2004. Estimated *S*, *U*, and *V* are lower bounds to the value of the relationship as a whole, to the buyer, and to the seller respectively. Details on the computation of *S*, *U*, and *V* are given in Section IIIA.

Source: Authors' calculations from customs records. See online Appendix A for data sources.

With many workers missing, firms suffered large reductions in total output. Online Appendix C, Figure A2 plots de-seasonalized export volumes around the period of the violence for the two separate groups of firms. The figure illustrates that the outbreak of the violence was a large and negative shock to the quantity of roses exported by the firms in the conflict locations.

In the survey, we asked several questions about whether the violence had been anticipated or not. Not a single firm among the 74 producers interviewed reported to have anticipated the shock and to have adjusted production or sales plans accordingly. The violence was a large, unanticipated, and short-run shock to the production function of firms.

D. *Relationship Characteristics*

Using the export customs data, we build a dataset of buyer-seller relationships. Overall, we focus on the period August 2004 to August 2008, i.e., four entire seasons. The violence occurred in January 2008, in the middle of the fourth season in the data.

We define the baseline sample of relationships as those links between an exporter (seller) and a foreign buyer that were active in the period prior to the violence. A relationship is active if the two parties transacted at least 20 times in the 20 weeks before the eruption of the violence. The data shows clear spikes in the distribution of shipments across relationships at one, two, three, four, and six shipments (transactions) per week in the relevant period. The cutoff is chosen to distinguish between established relationships versus sporadic orders. Results are robust to alternative cutoffs.

In total, this gives 189 relationships in the baseline sample. Table 1, panel A, reports summary statistics for the relationships in the baseline sample. The average

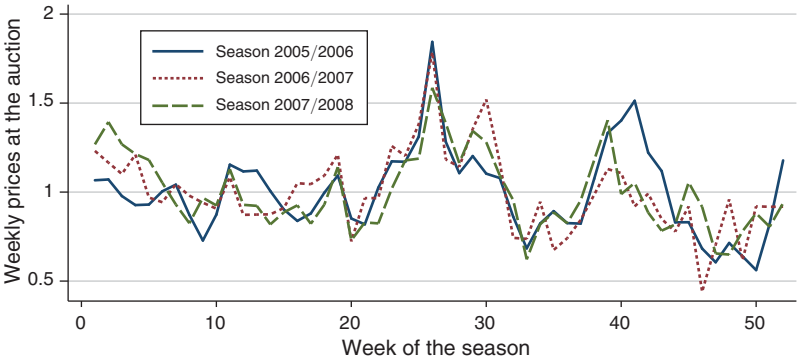

Figure 1. Seasonal Fluctuations in Auction Prices Are Predictable

Notes: The figure shows that FOB prices at the auctions are highly predictable. A regression of the weekly price at the auction on week and season dummies explains 70 percent of the variation in prices in the three seasons preceding the violence period. The flower industry classifies that a season begins in mid-August. For data sources, please refer to the online Appendix.

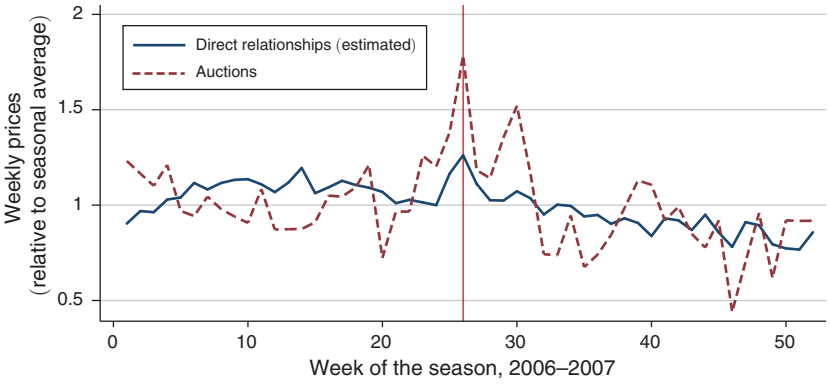

Figure 2. Fluctuations in Prices: Direct Relationships versus Auction

Notes: The figure shows that FOB prices in direct relationships are more stable than prices at the auctions throughout the season. The figure depicts the weekly variation relative to the season mean of FOB prices in direct relationships and at the auction. The FOB prices in direct relationships are obtained as week dummies in a regression of FOB prices on relationship fixed effects on the corresponding season. A season begins in mid-August. For data sources, please refer to the online Appendix.

relationship had 60 shipments in the 20 weeks preceding the violence. Immediately before the violence, contracting parties in the average relationship had transacted with each other 310 times. The first shipment in the average relationships occurred nearly two and a half years (830 days) before the beginning of the sample period.[7]

Exporters tend to specialize in one marketing channel. The majority of exporters either sells more than 90 percent of their produce through direct relationships, or

[7]These averages are left-censored, since they are computed from August 2004 onward. Since our customs export records begin in April 2004, we are able to distinguish relationships that were new in August 2004 from relationships that were active before. Among the 189 relationships in the baseline sample, 44 percent are classified as censored, i.e., were already active before August 2004. This confirms the findings of the survey, in which several respondents reported to have had relationships longer than a decade.

through the auctions. As a result, among the 100 established exporters, only 56 have at least one direct relationship with a foreign buyer. On average, exporters in the sample have three direct relationships (see Table 1, panel B). Similarly, there are 71 buyers with at least a relationship. The average buyer has about two and a half Kenyan suppliers.

Figures 1 and 2 document stylized facts that guide the formulation of the model. Figure 1 shows that prices at the auctions are highly predictable.

Figure 2 shows that prices in relationships are more stable than prices at the auctions.

II. Theory

We now present a model of the relationship between a rose producer (seller) and a foreign buyer (buyer). The setup of the model matches qualitative features of the market under consideration. The model is analyzed under three scenarios: (i) the benchmark case with no contract enforcement; (ii) an extension with uncertainty over the seller's type; and, finally, (iii) an extension to examine seller's reaction to the violence. These three different scenarios are used to derive the three tests we conduct in the empirical section. We first turn to a version of the model with no contract enforcement, developed along the lines of the relational contracts literature (see, e.g., MacLeod and Malcomson 1989; and Levin 2003). The incentive compatibility constraints of the model clarify how observable data on quantities transacted, prices in the relationships, and auction prices, can be used to compute lower bounds to the value of the relationship for the buyer and the seller. The model yields a test to establish whether the volume of trade in the relationship is limited by incentive compatibility constraints implied by the lack of contract enforcement (Test 1). The model is then extended to consider uncertainty over the seller's type. In contrast to the case without uncertainty, the extension predicts a positive correlation between the value and the age of the relationship (Test 2). Finally, we study how reputational forces influence the seller's reaction to the negative shock induced by the violence. Consistent with the interviews in the field, we model the violence as an unanticipated and observable shock that makes it impossible to deliver roses unless the seller undertakes additional unobservable effort (e.g., hire extra security, set up camps to host workers menaced by the violence). The model predicts an inverted-U shaped relationship between deliveries at the time of the violence and age of the relationship (Test 3).[8]

A. *Setup and First Best: Perfectly Enforceable Contracts*

Time is an infinite sequence of periods t, $t = 0, 1, \ldots$. The buyer and the seller have an infinite horizon and share a common discount factor $\delta < 1$. Periods alternate between high seasons $t = 0, 2, \ldots$, and low seasons $t = 1, 3, \ldots$. Low season variables and parameters are denoted with a lower bar (e.g., $\underline{x}$). Similarly, high season variables and parameters are denoted with an upper bar (e.g., $\overline{x}$).

[8] Section IV discusses alternative modeling assumptions. All proofs are in online Appendix B (Theory).

In each period, the seller can produce q units of roses at cost $c(q) = \frac{cq^2}{2}$. The buyer's payoffs from sourcing q units of roses from this particular seller is $r(q) = vq$ if $q \leq q^*$ and $r(q) = vq^*$ otherwise. The parameter v captures the buyer's willingness to pay for roses to be sold in the downstream market. The kink at q^* captures the buyer's desire for reliability. For simplicity, we assume $\underline{q}^* = \overline{q}^* = q^*$, i.e., the buyer's desired quantity of flowers is constant across seasons.

There is also a spot market where buyers and sellers can trade roses, the auction. The price at which sellers can sell, p_t^m, oscillates between $p_t^m = \overline{p}$ in high seasons and $p_t^m = \underline{p} < \overline{p}$ in low seasons. The buyer can purchase roses at the auctions at price $p_t^b = p_t^m + \kappa$, with $\kappa > 0$ capturing additional transport and intermediation costs.

For expositional clarity, it is worth considering the case with perfect contract enforcement first. Consistent with practices in the industry, we assume that contracts are negotiated at the beginning of each high season. Parties agree on constant prices for the high season and the subsequent low season.[9] A contract negotiated in period t, then, is given by $\mathcal{C}_t = \left\{\overline{q}_t, \underline{q}_{t+1}, w_t\right\}$. The contract specifies quantities to be delivered in the high season t, $\overline{q}_t$, in the following low season, $\underline{q}_{t+1}$, and a unit price to be paid upon delivery of roses in each season, w_t.

The seller can sell at the auctions and to the buyer simultaneously. Contracts with the buyer cannot be contingent on the seller's sales at the auctions. The buyer has all the ex ante bargaining power. The buyer offers a contract to maximize her profits across two subsequent high and low seasons subject to the seller participation constraint. We denote the optimal contract $\mathcal{C}_t^* = \left\{\overline{q}_t^*, \underline{q}_{t+1}^*, w_t^*\right\}$.

We assume that (i) the buyer never buys at the auctions ($\kappa > v$); (ii) trade between the seller and the buyer is efficient in both seasons ($v > \overline{p}$); and (iii) it is efficient for a seller supplying q^* to the buyer to sell at the auctions in the high season ($\overline{p} > cq^*$) but not in the low season ($cq^* > \underline{p}$). We normalize $\underline{p} = 0$ and omit the period subscript t when this does not create confusion.

Under these assumptions, the optimal contract displays two features that characterize the data. First, there are lower seasonal fluctuations in the sales to the buyer than in the sales to the auctions. Second, there is price compression: the price in the relationship lies in between auction prices in the high and low seasons, $\underline{p} < w^* < \overline{p}$. In a relationship with perfect contract enforcement the optimal contract is repeated forever.

B. *No Enforcement*

As revealed by interviews in the field, contracts enforcing the delivery of roses are not available. This, potentially, generates two problems. First, the buyer might refuse to pay the seller once the roses have been delivered. Second, the seller might fail to deliver the quantity of roses agreed with the buyer. Buyers and sellers use relational contracts to overcome lack of enforcement.

[9] The complexity associated with indexing contracts on weekly auction prices and the desire to smooth income profiles are likely forces behind the use of constant prices. We abstract from these forces and take constant prices as a fact of commercial life in our environment.

A relational contract is a plan $\mathcal{C}^R = \left\{ \overline{q}_t, \underline{q}_{t+1}, w_t \right\}_{t=0,2,\ldots}^{\infty}$ that specifies quantities to be delivered, $\overline{q}_t$ and $\underline{q}_{t+1}$, and unit prices, w_t, for all future high and low seasons. Parties agree to terminate the relationship and obtain their outside options forever following any deviation. The outside option of the seller, denoted V_t^O, is to sell at the auctions forever. The outside option of the buyer is exogenously given and denoted U_t^O.[10]

Given the crucial role played by the incentive compatibility constraints in the empirical analysis, it is worth describing them in detail. Denote with U_t and V_t the net present value of the payoffs from the relationship at time t for the buyer and the seller respectively. The buyer must prefer to pay the seller rather than terminating the relationship, i.e.,

$$\delta\left(\underline{U}_{t+1} - \underline{U}_{t+1}^O\right) \geq w_t \times \overline{q}_t \text{ for all } t = 0, 2, \ldots \tag{1}$$

in the high seasons and

$$\delta\left(\overline{U}_{t+2} - \overline{U}_{t+2}^O\right) \geq w_t \times \underline{q}_{t+1} \text{ for all } t = 0, 2, \ldots \tag{2}$$

in the low seasons.

Similarly, the seller must prefer to produce and deliver the roses to the buyer rather than selling at the auctions. In the high seasons, the seller produces roses for the auctions regardless of the relational contract with the buyer. The seller's best deviation, therefore, is to side-sell to the spot market roses produced for the buyer, i.e.,

$$\delta\left(\underline{V}_{t+1} - \underline{V}_{t+1}^O\right) \geq \left(\overline{p} - w_t\right)\overline{q}_t \quad \text{for all } t = 0, 2, \ldots \tag{3}$$

In the low seasons, instead, the seller never sells to the auctions. The seller's best deviation is to not produce, i.e.,

$$\delta\left(\overline{V}_{t+2} - \overline{V}_{t+2}^O\right) \geq -\left(w_t \times \underline{q}_{t+1}\right) + c(\underline{q}_{t+1}) \quad \text{for all } t = 0, 2, \ldots \tag{4}$$

The buyer offers a relational contract $\mathcal{C}^R$ to maximize the discounted value of future profits subject to (1), (2), (3), and (4).[11] We denote the optimal relational contract $\mathcal{C}_t^{R^*} = \left\{ \overline{q}_t^R, \underline{q}_{t+1}^R, w_t^R \right\}$.

The optimal contract still features price compression, i.e., $\underline{p} < w_t^R < \overline{p}$. Price compression implies that (4) is never binding while (3) always is. Summing the two constraints (1) and (3) we can write

$$\delta\left(\underline{S}_{t+1}^R\right) \geq \overline{p}_t \times \overline{q}_t, \tag{5}$$

[10] Given the assumption that the buyer never purchases at the auctions ($\kappa > v$), the buyer's outside option is to search, possibly at some additional costs, for alternative suppliers. For simplicity, we do not endogenize the value of the buyer's outside option.

[11] Constraint (3) and the assumption that the seller's outside option is to sell forever at the auctions imply that the seller's participation constraint is satisfied.

where $\underline{S}^R_{t+1} = \underline{V}_{t+1} + \underline{U}_{t+1} - \underline{V}^O_{t+1} - \underline{U}^O_{t+1}$ is the value of the future rents generated by the relationship—henceforth, the value of the relationship.

Lack of enforcement, therefore, implies that the amount of roses traded in the high seasons, $\overline{q}^R_t$, might be constrained by the future value of the relationship. The incentive constraint (5) illustrates how data on auction prices $\overline{p}_t$ and volumes of trade in the high seasons, $\overline{q}^R_t$, both directly observed in the data, can be used to (i) estimate a lower bound to the value of the relationship, denoted $\hat{S}_t$, and (ii) test whether the incentive constraint (5) and, by implication, both incentive constraints (1) and (3), are binding.[12] The logic of the test is as follows. The future value of the relationship, $\hat{S}_{it}$, does not depend on current auction prices. If (5) is binding, therefore, a small and unanticipated increase in prices at the auctions should lead to a corresponding decrease in the quantity traded, $q^R_{i,t\omega^*_{it}}$. In particular, holding $\delta\left(\underline{S}^R_{t+1}\right)$ constant and taking logs, a binding constraint (5) implies an elasticity equal to minus one between $q^R_{i,t\omega^*_{it}}$ and prices at the auctions $p_{i,t\omega^*_{it}}$. This observation, suggests a test for whether the incentive constraint (5) is binding, i.e., for whether the volume of trade is constrained by the future value of the relationship. This gives us:

Test 1: *If lack of enforcement constrains the volume of trade in the relationship the elasticity of the quantity of roses traded in the high season to auction prices equals minus one.*

The analysis in the empirical section reveals that the volume of trade in the relationships is constrained by lack of enforcement. The model yields an additional prediction: the quantity traded in the high season $\overline{q}^R_t$ and the value of the relationship do not depend on the age of the relationship. This prediction directly follows from well-known results in the literature that the optimal relational contract is stationary (see, e.g., MacLeod and Malcomson 1989; and Levin 2003). The data reject this prediction of the model. This leads to the next extension of the model in which uncertainty over the seller's type is introduced.

C. *No Enforcement and Uncertainty about the Seller's Type*

Interviews in the field suggest that concerns over a seller's reputation for reliability are of paramount importance among buyers and sellers. First, delays and irregularity in rose deliveries are costly to the buyer. Second, the sector has expanded rapidly and many sellers lack a previous record of success in export markets.[13]

The literature has formalized reputational concerns by introducing uncertainty over players' type. We introduce uncertainty about the seller's reliability as follows. There are two types of sellers: reliable and unreliable. A reliable seller can always deliver flowers to the buyer. An unreliable seller, instead, is subject to temporary

[12] Similarly, the incentive constraints (1) and (3) illustrate how data on auction prices $\overline{p}_t$, relationship's volumes in the high season $\overline{q}^R_t$, and prices w^R_t can be used to estimate lower bounds to the value of the relationship for the buyer (given by $\hat{U}_t = w^R_t \overline{q}^R_t$) and for the seller (given by $\hat{V}_t = \left(\overline{p}_t - w^R_t\right)\overline{q}^R_t$). The lower bound estimate of the value of the relationship, $\hat{S}_t$, is given by $\hat{S}_t = \hat{U}_t + \hat{V}_t$.

[13] Buyers must, of course, also develop a reputation for respecting contracts. Relative to suppliers, which are all clustered in a handful of locations, buyers are scattered in several destination countries. Suppliers, therefore, can share information about cheating buyers more easily than buyers can share information about cheating suppliers. As a result, uncertainty over a seller's reliability might be more relevant than uncertainty over buyer's reliability.

shocks that make delivery of roses to the buyer impossible. These shocks can be interpreted as delivery failures that occur because of problems in harvesting, cooling, or transporting roses. These problems are difficult to control due to inadequate technology or to agency problems between the seller and her workers. The probability of a shock conditional on the seller being an unreliable type, λ, is known to both parties and is constant over time. The type of the seller is unknown to both parties. At the beginning of the relationship, both the buyer and the seller believe that the seller is reliable with probability θ_0.

Within each period the timing of events is as follows. First, the seller produces and incurs costs according to her production plan. After having produced, the seller observes whether the negative shock has been realized. If the shock has been realized, the produced roses are not suitable for delivery to the buyer. All roses are then sold at the auctions and the seller learns to be the unreliable type.[14] If no shock is realized, the seller updates beliefs and decides whether to sell roses to the buyer as specified in the relational contract or side-sell to the auctions.

Contract terms, trade outcomes, and relationship's length are not observed by other market participants. The seller's outside option, V_t^0, is to sell on the market forever, as before. We assume that the buyer's outside option, U_t^0, is larger than the value of a relationship in which beliefs about the seller's type are sufficiently pessimistic.

Over time the buyer observes the history of delivery realizations and updates beliefs. Consider an equilibrium in which the seller delivers flowers whenever there has been no shock. In such an equilibrium, after the first delivery failure, the buyer immediately believes the seller to be unreliable and terminates the relationship.[15] After τ consecutive deliveries both parties hold beliefs θ_τ given by

$$\theta_\tau = \frac{\theta_0}{\theta_0 + (1 - \theta_0)(1 - \lambda)^\tau}, \tag{6}$$

with $\theta_{\tau+1} > \theta_\tau$ for all τ and $(\theta_{\tau+1} - \theta_\tau) > (\theta_{\tau+2} - \theta_{\tau+1})$ for all τ sufficiently large. This last observation implies that after a certain point, additional deliveries have a decreasing positive impact on beliefs as uncertainty over the seller's type vanishes. The expected probability of delivery is given by $\mu_\tau = \theta_\tau + (1 - \theta_\tau)(1 - \lambda)$.

The analysis of this model is similar to the one in the previous section. The possibility of learning, however, introduces dynamics into the model. Expected per period surplus at age τ is increasing in the probability of delivery μ_τ. Conditional on a history of consistent delivery, the expected value of the relationship at age τ, $S^R(\theta_\tau)$, increases over time. If beliefs θ_τ are such that the constraint (5) is binding, the quantity traded in the high seasons, $\overline{q}^{R^*}(\theta_\tau)$, and the relationship value, S_τ, increase with the age of the relationship. As mentioned above, the analysis in the

[14] This assumption is made for both realism and simplicity. Roses that are not suitable for delivery to the buyer, e.g., because of minor delays or packaging problems, can still be sold at the auctions, possibly at a discount. Ignoring the discount simplifies the algebra without altering the main results.

[15] In such an equilibrium, therefore, the seller never has more information than the buyer during the course of the relationship. This greatly simplifies the analysis.

empirical section reveals that the volume of trade in the relationships is constrained by lack of enforcement, i.e., (5) is binding (Test 1). This leads to the following:

Test 2: *Lack of enforcement and learning about the seller's type imply the value of the relationship increases with the age of the relationship. In contrast, lack of enforcement alone implies the value of the relationship does not correlate with the age of the relationship.*

The evidence in Section III supports the predictions of the model with uncertainty over the seller's type. Analyzing how the relationship responds to the violence offers an opportunity to derive further predictions from the model with uncertainty over the seller's type and distinguish it from alternative mechanisms.[16]

D. *Maintaining Reputation During the Violence*

The electoral violence occurred in the middle of the high season, a few weeks before the Valentine's Day peak. We assume the violence occurs after production plans have been executed, production costs incurred, and a fraction $\gamma \in (0,1)$ of planned sales already delivered. Consistent with interviews conducted in the field, we model the violence as an observable and unanticipated shock that made it harder for sellers to deliver roses. The violence was a highly unusual event. During the violence sellers could undertake a variety of costly actions to mitigate the resulting disruptions and enhance the chances of delivering roses as usual. For example, sellers could (i) stop selling flowers to the auctions; (ii) set up camps to temporarily host workers menaced by the violence so that roses could be harvested on time; and (iii) hire extra security and coordinate transport with other firms. These actions are not relevant during normal business activity and, therefore, are not included in the baseline model of the previous sections. The empirical section concludes providing direct evidence consistent with firms having undertaken this type of action to mitigate the negative effects of the violence.

The amount of resources invested to mitigate the effects of the violence is difficult to monitor for foreign buyers. For simplicity, we model those actions as unobservable effort e that enhances the likelihood of delivery. Specifically, we assume that a seller exerting effort e has a probability of completing delivery equal to $(\mu_\tau \cdot e)$.[17] This assumption means that a seller not exerting effort has no chances of completing delivery of roses during the violence. The costly effort, however, mitigates the consequences of the violence and, in the limit, restores deliveries as usual when $e \to 1$. The cost of effort is given by $\Gamma(e)$ and is assumed to satisfy properties guaranteeing the existence of an interior equilibrium.[18]

[16] Other mechanisms, however, are also potentially consistent with the dynamics predicted by the model with learning. For example, there could be "learning by trading", in which parties accumulate capital that is specific to the relationship and increase the amount of flowers transacted over time.

[17] Recall that μ_τ is the expected probability of delivery under normal circumstances in a relationship of age τ. For simplicity, we assume that the negative reliability shock hits the unreliable type with probability λ after $\gamma \underline{q}^R_\tau$ roses have been delivered. This assumption captures in a parsimonious way the timing of the violence and ensures deliveries at the time of the violence are informative about the seller's type.

[18] Namely, $\Gamma'(\cdot) \geq 0$, $\Gamma''(\cdot) > 0$, $\Gamma'(0) = 0$ and $\lim_{e \to 1} \Gamma'(e) = \infty$.

We are interested in deriving predictions between deliveries during the violence and the age of the relationship τ. Denote by $\tilde{e}_\tau$ the buyer's beliefs about the effort exerted by the seller. In the equilibrium: (i) given buyer's beliefs, the seller exerts effort e_τ to maximize expected payoffs, and (ii) buyer's beliefs are correct. The buyer observes whether roses have been delivered ($d = 1$) or not ($d = 0$) and, given prior beliefs θ_τ and about effort $\tilde{e}_\tau$, updates posterior beliefs about the seller's type, $\theta^d_{\tau+1}$, using Bayes' rule.

Delivery of the remaining share $(1 - \gamma)$ of planned roses occurs only if a negative reliability shock is not realized. Conditional on delivery completion, posterior beliefs, $\theta^{d=1}_{\tau+1}$, are independent of the buyer's beliefs $\tilde{e}_\tau$ and identical to the beliefs the buyer would have had had the violence not occurred. Following a delivery, then, the relationship continues as originally planned.[19] Posterior beliefs following a delivery failure, $\theta^{d=0}_{\tau+1}$, must be more pessimistic. For any buyer's beliefs $\tilde{e}_\tau > 0$, a delivery failure could still be caused by the negative reliability shock. This implies $\theta^{d=0}_{\tau+1} < \theta_\tau$. In contrast to the case of no violence, however, a delivery failure does not necessarily reveal the seller to be an unreliable type since the failure could also be due to the violence ($\tilde{e}_\tau < 1$). The buyer ends the relationship only if posterior beliefs are sufficiently pessimistic. When this is the case, both parties receive their outside option.

Denote $V^D(\theta^d_{\tau+1})$ the seller's payoff after delivery ($d = 1$) and after non-delivery ($d = 0$). The seller chooses e_τ to maximize her payoff taking as given the buyer's beliefs. The seller solves

$$e_\tau \in \arg\max_e \; e\mu_\tau V^D(\theta^{d=1}_{\tau+1}) + \left(1 - e\mu_t\right) V^D(\theta^{d=0}_{\tau+1}) - \Gamma(e) \tag{7}$$

which yields first order condition

$$\mu_\tau\left(V^D(\theta^{d=1}_{\tau+1}) - V^D(\theta^{d=0}_{\tau+1})\right) = \Gamma'(e_\tau). \tag{8}$$

Inspection of the first order condition reveals that incentives to exert effort are initially increasing in τ. Intuitively, for sufficiently low τ, a delivery failure leads to pessimistic beliefs and to the end of the relationship. At early stages, older relationships are both associated with higher returns to effort μ_τ and higher continuation values for the seller, $V^D(\theta^{d=1}_{\tau+1})$. However, in sufficiently old relationships, the buyer is very confident about the seller's type and observed deliveries do not affect the buyer's beliefs. The continuation values for the seller following a delivery and a delivery failure get closer and incentives to exert effort vanish.[20] This leads to the following:

Test 3: *The likelihood of delivery during the violence is inverted-U shaped in the age of the relationship.*

[19] In particular, note that the binding incentive constraint (5) implies the buyer cannot further incentivize delivery during the violence. Given posterior beliefs, the buyer would renege on any promise of higher prices or of a higher continuation value to the seller following a delivery at the violence.

[20] This provides the intuition for the result. The formal proof must take into account the endogenously determined buyer's beliefs about effort $\tilde{e}_\tau$. See online Appendix B for details.

E. *Summary*

The model provides the following three tests:

Test 1: *If lack of enforcement constrains the volume of trade in the relationship the elasticity of the quantity of roses traded in the high season to auction prices equals minus one*.

Test 2: *Lack of enforcement and learning about the seller's type imply the value of the relationship increases with the age of the relationship. In contrast, lack of enforcement alone implies the value of the relationship does not correlate with the age of the relationship*.

Test 3: *Lack of enforcement and learning about the seller's type predicts an inverted-U shaped relationship between deliveries at the time of the violence and relationship's age.*

III. Empirical Results

This section presents the empirical results. We begin by introducing notation and describing how we compute key variables for the empirical tests. We then turn to the three tests derived in the theory section: (i) is the volume of trade constrained by lack of enforcement? (Test 1); (ii) does the value of the relationship increase with age? (Test 2); and (iii) are deliveries during the violence an inverted-U shaped function of relationship's age, as predicted by the reputation model? (Test 3). Finally, we conclude by providing direct evidence of the effort exerted by sellers to protect valuable relationships during the violence.

A. *Incentive Constraints and the Value of Relationships*

The first two empirical tests derived in the theory section are based on the incentive compatibility constraint (5). From an empirical point of view, the appeal of the incentive constraints is that volumes of roses traded in the relationship, $\overline{q}_t^R$, and auction prices, $\overline{p}$, are directly observable in the data. Besides allowing us to derive a simple test for whether lack of enforcement constraints the volume of trade in the relationship, the incentive constraint also allows us to compute a lower bound to the value of the relationship. This lower bound does not rely on information on cost structures and expectations of future trade which are typically unobservable and/or difficult to estimate.

Before bringing the incentive constraint (5) to the data it is useful to introduce some notation. In line with practices in the industry, business seasons (denoted with t) start in mid-August. For example, the violence occurred in the middle of the fourth season for which we have data. Each season counts 52 weeks (denoted with $\omega \in \{1, 2, \ldots, 52\}$). We denote sellers with subscript s, buyers with subscript b, and relationships (i.e., pairs of sellers and buyers) with subscript i. We will use seller s and buyer b subscripts in cross-sectional specifications and relationship subscripts i in panel specifications that allow to control for relationship fixed effects. With this

notation, $q^R_{i,t\omega}$ will denote the quantity traded in relationship i and $p_{i,t\omega}$ the relevant auction price in week ω of season t. Note that auction prices, $p_{i,t\omega}$, are indexed by i since different relationships trade different types of roses that are sold at the auctions at different prices.[21]

Recall the model implies that only the incentive constraint corresponding to the maximum temptation to deviate in each season has to be considered. For each relationship i and season t, therefore, we focus on the time in which the value of roses traded in the relationship and valued at market prices is highest. A season in the model is defined by two consecutive periods with alternating high and low prices. In practice, however, a season is a sequence of 52 weeks. Recall that in the model any deviation from either the buyer or the seller leads to the termination of the relationship. In taking the model to the data, therefore, we need to choose the length of the period after which the relationship is terminated if any party deviates. We chose a week and show below that results are robust to the choice of longer windows.

For each relationship i in season t, define week ω^*_{it} as the week of season t for which the value of roses traded in relationship i and valued at market prices $p_{i,t\omega}$ is highest, i.e.,

$$\omega^*_{it} = \arg\max_{\omega} \left\{ q^R_{i,t\omega} \times p_{i,t\omega} \right\}. \tag{9}$$

The lower bounds to the value of relationship i in season t, denoted by $\hat{S}_{it}$, is then given

$$\hat{S}_{it} = q^R_{i,t\omega^*_{it}} \times p_{i,t\omega^*_{it}}. \tag{10}$$

$\hat{S}_{it}$ and $q^R_{i,t\omega^*_{it}}$ are the two main variables on which Test 1 and Test 2 are performed.[22]

The estimated value of the relationships, $\hat{S}_{it}$, is our main outcome variable for Test 1 and Test 2. The tests exploit variation in $\hat{S}_{it}$ across seasons t and relationships i. The tests are conducted under a variety of empirical specifications that control for combinations of relationship, season, and seasonality fixed effects. Before describing the results, it is therefore useful to illustrate the sources of variation in $\hat{S}_{it}$. There are three main sources of variation in $\hat{S}_{it}$: (i) the time of season t during which the market value of roses traded in relationship i is highest, ω^*_{it}; (ii) the prices at the auctions during the window ω^*_{it}, $p_{i,t\omega^*_{it}}$; and (iii) the quantities transacted during the window ω^*_{it}, $q^R_{i,t\omega^*_{it}}$.

Figure 3 illustrates the first source of variation by reporting the distribution of weeks ω^*_{it} in the sample of relationships active in the season before the violence. The week of Valentine's Day is the time during which the market value of roses traded in relationship i is highest for about 40 percent of relationships. Other prominent

[21] We only know the average weekly prices at the auctions for large and small roses. We derive a relationship specific auction price $p_{i,t\omega}$ using a weighted average of prices for large and small roses with weights given by the average unit weight of roses traded in the relationship. We show below results are robust to different choices of the weights.

[22] As noted in footnote 12, the individual incentive compatibility constraints for the buyer (1) and for the seller (3) yield lower bounds to the value of the relationship for each party. Denoting $w_{i,t\omega}$ the price paid in relationship i in week ω of season t, these values are respectively given by $\hat{U}_{it} = q^R_{i,t\omega^*_{it}} \times w_{i,t\omega^*_{it}}$ and $\hat{V}_{it} = q^R_{i,t\omega^*_{it}} \times \left(p_{t\omega^*_{it}} - w_{i,t\omega^*_{it}}\right)$. Note that if (5) is binding, then both (1) and (3) must be binding and the lower bounds provide exact estimates to the value of the relationship for each party. Table 4 reports results on these outcomes too.

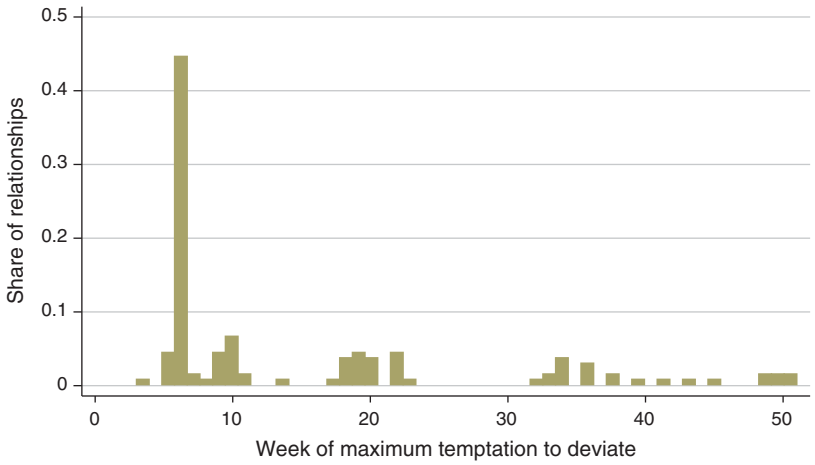

FIGURE 3. DISTRIBUTION OF HIGHEST TEMPTATION WEEKS

Notes: The figure shows the distribution of the calendar weeks in which the incentive constraint is more likely to bind. This is given by the week of the season in which the value of roses traded in the relationship and valued at auction prices is highest. The sample is given by all the relationships active in the season before the violence.

weeks are around Mother's or Women's Days, which typically fall in March (e.g., the United Kingdom, Russia, Japan) or later in May (e.g., other European countries and the United States) depending on the country. In the reminder of the analysis, seasonality is controlled for by including dummies for the week of the season ω^*_{it}.

The second source of variation, $p_{i,t\omega^*_{it}}$, combines variation in the price of roses at the auctions and in the unit weight of roses traded in the relationship during the window ω^*_{it}. Since unit weights of roses traded within a given relationship are relatively stable over time, the main source of variation is given by auction prices.[23] Figures 1 and 2 show seasonal variation in average prices at the auctions. Variation in $p_{i,t\omega^*_{it}}$ across seasons and relationships, however, is also driven by variation in the relative auction prices of large and small roses. Figure 4 shows a significant amount of variation in the relative price of large and small roses at the auctions both within and across seasons. For example, during the Valentine's Day week, the ratio of prices for large and small roses has varied from 1.39 to 1.72 in the three seasons before the violence.

Figure 5 illustrates the third source of variation by reporting the distribution of quantities traded during the window ω^*_{it}, $q^R_{i,t\omega^*_{it}}$, in the sample of relationships active in the season before the violence. The quantity $q^R_{i,t\omega^*_{it}}$ is normalized by the average weekly quantity traded in the relationship during the season. The median relationship has a ratio just above 2, and there is substantial variation across relationships with values from 0.83 to 7.05.[24]

For the 189 relationships in the baseline sample, Table 1, panel C shows that the aggregate value of the relationship $\hat{S}_{it}$ in the season that preceded the violence was

[23] We show below that results are robust to holding constant the unit weight of roses sold in the relationship.

[24] For most relationships the window ω^*_{it} falls at times of particularly high demand, such as Valentine's Day. This implies that the ratio is larger than one for most relationships.

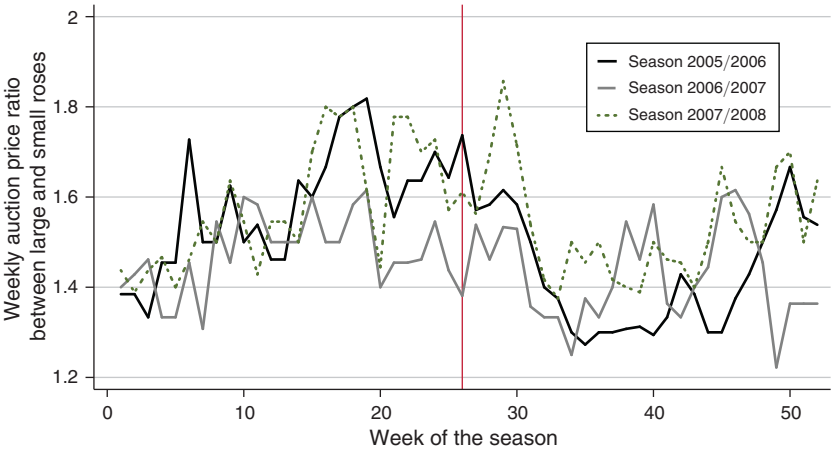

FIGURE 4. VARIATION IN PRICES OF LARGE AND SMALL ROSES AT THE AUCTION

Notes: This figure depicts the evolution of the ratio of prices for large and small roses at the auctions in the three seasons preceding the violence. At the time of the Valentine's Day week, week 26 (referenced by vertical line), when for most relationships the incentive constraint is most likely to be binding (see Figure 3), the ratio of prices for large and small roses has varied from 1.39 to 1.72 in the three seasons in our sample.

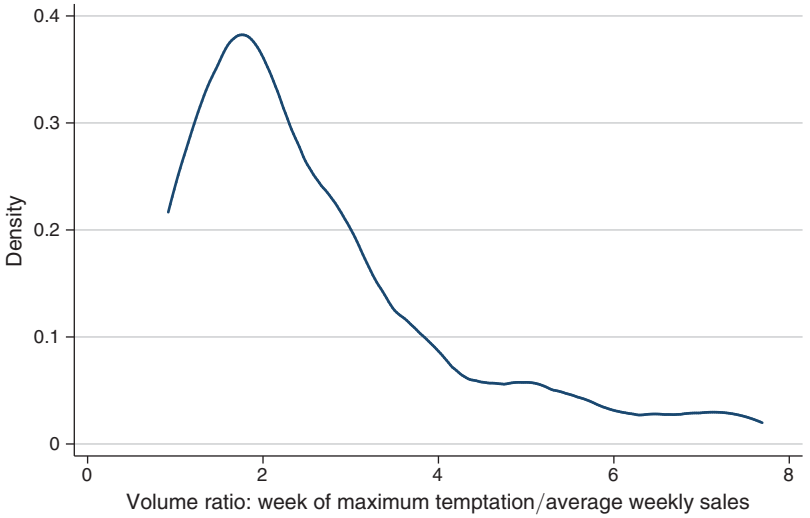

FIGURE 5. STRETCH IN VOLUMES AT THE MAXIMUM TEMPTATION TO DEVIATE

Notes: The figure shows the distribution of the ratio between the volume of roses traded in the week in which the incentive constraint is more likely to bind and the average weekly sales in the relationship. The sample is given by all the relationships active in the season before the violence.

384 percent of the average weekly revenues in the average relationship. The values for the buyer $\hat{U}_{it}$ and seller $\hat{V}_{it}$ respectively are 270 percent and 161 percent of average weekly revenues.[25]

[25] Under free-entry, initial sunk investments dissipate the ex post rents generated by the relationship (see, e.g., Shapiro 1983). The estimates yield a lower bound to the fixed costs of starting a relationship and can be compared

Table 2—Binding Incentive Compatibility Constraint (Test 1)

	Trade volume (1)	Relationship value (2)	Price (3)
Price at auction (ln)	−0.936**	0.064	0.313
	(0.371)	(0.371)	(0.193)
Relationship fixed effects	Yes	Yes	Yes
Season fixed effects	Yes	Yes	Yes
Seasonality fixed effects	Yes	Yes	Yes
Adjusted R^2	0.861	0.867	0.606
Observations	430	430	430

Notes: The table reports correlations between prices at the auctions and relationship outcomes at the time of the maximum temptation to deviate. A binding incentive compatibility constraint implies a minus one elasticity of quantity of roses traded in the relationship with respect to auction prices at the time of the largest temptation to deviate (Test 1). All variables are in logs. The outcomes are computed for all seasons before the violence and the sample refers to relationships that were active during the period. The sample excludes relationships that are in the baseline sample but were not active in the season preceding the violence and includes relationships that did not survive until the violence season. Following business practices in the industry, a season starts in mid-August. The three considered seasons are those starting in August 2004, 2005, and 2006. Seasonality fixed effects are dummies for the week of the season in which the maximum aggregate temptation to deviate occurs. Robust standard errors, clustered at the firm level are reported in parenthesis.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

B. *Test 1: Binding Incentive Constraint*

The first test we address is whether the incentive constraint (5) is binding (Test 1). A binding incentive constraint (5) would imply that lack of enforcement constrains the amount of flowers traded in the relationship. The logic of the test is as follows. The future value of the relationship, $\hat{S}_{it}$, does not depend on current auction prices. If (5) is binding, therefore, a small unanticipated increase in prices at the auctions should lead to a corresponding decrease in the quantity traded, $q^R_{i,t\omega^*_{it}}$. There should be an elasticity equal to minus one between $q^R_{i,t\omega^*_{it}}$ and prices at the auctions $p_{i,t\omega^*_{it}}$.

In taking this prediction to the data, we need to consider the nature of fluctuations in auction prices as well as the frequency of price changes. In the model, prices oscillate deterministically and are known in advance. In practice, although Figure 1 shows that much variation in auction prices is predictable, deviations from expected prices still occur. Furthermore, the future value of the relationship could depend on expectation of future prices. In the baseline specification in Table 2 we control for expectations about future auction prices by including both season and seasonality fixed effects. Seasonality fixed effects are accounted for by including dummies for the week of the season ω^*_{it} from which estimates are derived. The combination of season and seasonality effects implies that variation in prices at the auctions

to structural estimates of fixed costs of exporting. Das, Roberts, and Tybout (2007) report that in the Colombian chemicals industry, fixed costs of exports in each year represent 1 percent of the export revenues of the firm. The corresponding figure for the initial sunk costs is between 18 to 42 percent. Our estimates are a conservative lower bound since we focus on a temptation window of one week.

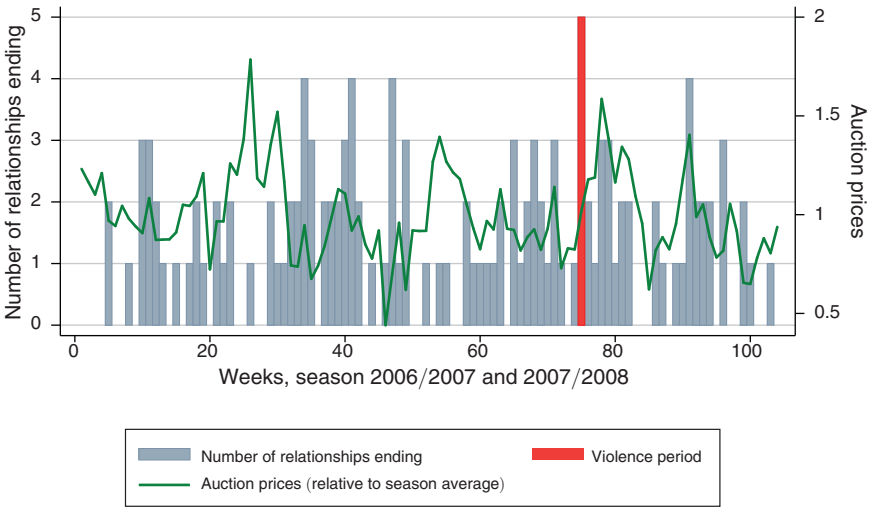

FIGURE 6. RELATIONSHIPS DO NOT END WHEN AUCTION PRICES ARE HIGH

Notes: The figure shows that the number of relationships ending in a given week does not correlate with the price at the auctions in that week during the three seasons preceding the violence. This is consistent with the fact that prices at the auctions are highly predictable. In a regression of the number of relationships dying in a given week that controls for week and season dummies, the coefficient on the violence period is positive and significant. The R^2 for the same regression is 0.57. Regardless of whether week dummies are controlled for or not, the level of prices at the auctions does not predict the number of relationships dying. For data sources, please refer to the online Appendix.

captures unanticipated variation around the expected prices. To keep closer to the model formulation, in which all price variation is known in advance, we also report results without controlling for season and seasonality fixed effects in Table 3.[26]

Table 2 reports correlations between prices at the auctions and quantity $q^R_{i,t\omega^*_{it}}$ (column 1) and relationship's value $\hat{S}_{it}$ (column 2). Controlling for relationship, season, and seasonality fixed effects, Table 2 shows that higher prices at the auctions lead to a proportional reduction in quantity traded (column 1) and that, as a result, the aggregate value of roses traded remains constant (column 2). The estimated elasticity between quantity $q^R_{i,t\omega^*_{it}}$ and auction prices is equal to (-0.936), which is very close to (and not statistically different from) the minus one implied by the binding incentive constraint (5). The model also implies that changing prices paid to the seller does not help relaxing the aggregate incentive constraint (5) since a reduction in the seller's temptation to deviate is compensated by an equal increase in the buyer's temptation, and vice-versa. Column 3 shows that, indeed, prices in the relationship at the time the constraint binds do not respond to auction prices.

Figure 6 provides further evidence consistent with the findings in Table 2 that parties adjust to unanticipated fluctuations in auction prices. The figure shows that the number of relationships ending in a given week does not correlate with price at the

[26] By including season, seasonality, and relationship fixed effects, all the variation in the price variable comes from how heavy, relative to previous relationship sales and other firms' sales in the same season and week, the roses traded are and the ratio of big/small rose prices at auction. A robustness check in Table 3 shows that the results are robust to hold constant unit weight of roses traded in the relationship. This reassures us that changes in the composition of traded roses at the time of particularly high prices do not drive the results.

Table 3—Binding Incentive Compatibility Constraint (Test 1): Robustness Checks

	Trade volume			Relationship value		
	(1)	(2)	(3)	(4)	(5)	(6)
Price at auction (ln)	−0.818***	−1.184***	−0.940**	0.182	−0.184	0.06
	(0.171)	(0.324)	(0.414)	(0.171)	(0.324)	(0.414)
Relationship fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Season fixed effects	Yes	No	Yes	Yes	No	Yes
Seasonality fixed effects	No	Yes	Yes	No	Yes	Yes
Constant unit weight	No	No	Yes	No	No	Yes
Adjusted R^2	0.847	0.842	0.856	0.854	0.849	0.863
Observations	430	430	430	430	430	430

Notes: The table reports correlations between prices at the auctions and relationship outcomes at the time of the maximum temptation to deviate. A binding incentive compatibility constraint implies a minus one elasticity of quantity of roses traded in the relationship with respect to auction prices at the time of the largest temptation to deviate (Test 1). All variables are in logs. The outcomes are computed for all seasons before the violence and the sample refers to relationships that were active during the period. The sample excludes relationships that are in the baseline sample but were not active in the season preceding the violence and includes relationships that did not survive until the violence season. Following business practices in the industry, a season starts in mid-August. The three considered seasons are those starting in August 2004, 2005, and 2006. Seasonality fixed effects are dummies for the week of the season in which the maximum aggregate temptation to deviate occurs. Constant unit weight specifications assign relevant auction prices to the relationship holding unit weights of roses traded in the relationship constant over time. Robust standard errors, clustered at the firm level are reported in parenthesis.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

auctions in that week during the seasons preceding the violence period. Regardless of whether week dummies are controlled for or not, the level of prices at the auctions does not predict the number of relationships ending.

Table 3 performs robustness checks. Columns 1 and 4 omit seasonality fixed effects, columns 2 and 5 omit season fixed effects. Columns 3 and 6, instead, repeat the exercise holding constant the unit weight of flowers traded in the relationship. The table shows that results are robust to using different sources of variation in the auction prices at the time of the highest temptation to deviate.

C. *Test 2: Relationship's Value and Age*

Table 2 provides evidence that lack of enforcement constrains the volume of roses traded. We now explore whether the value of the relationship correlates with the age of the relationship (Test 2). We begin with a graphic exploration. Figure 7 plots the distribution of the (logs of the) estimated values of the relationship, $\hat{S}_{it}$, for three different samples of relationships in the season before the violence: relationships in the baseline sample that were active at the Valentine's Day peak of the season prior to the violence; younger relationships in the baseline sample that were not yet active during the Valentine's Day peak of the season prior to the violence; and relationships that were active during the Valentine's Day peak of the season prior to the violence but that are not in the baseline sample since they did not survive until the violence period. Figure 7 shows two patterns: (i) young relationships had lower values than established relationships, and (ii) relationships that have survived have higher values than relationships that did not.

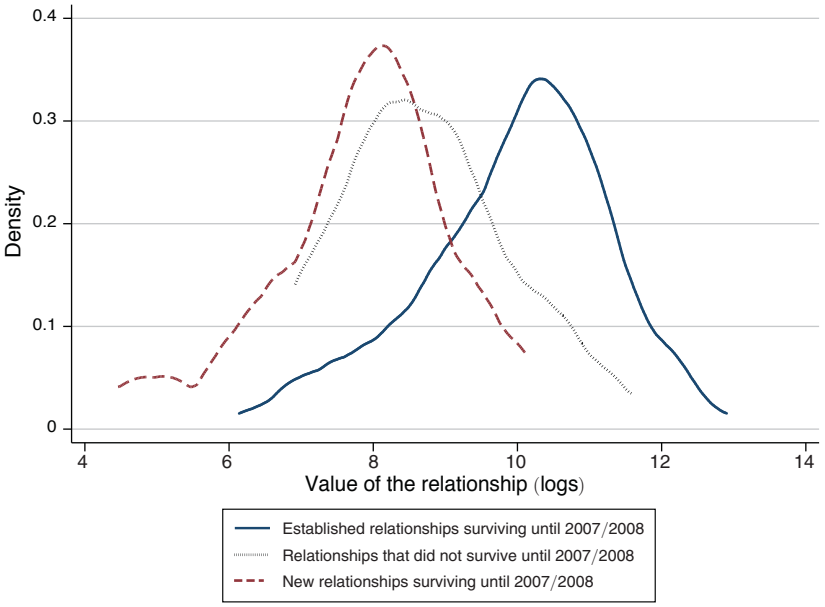

FIGURE 7. SURVIVING RELATIONSHIPS AFFORD HIGHER AGGREGATE TEMPTATIONS

Notes: The figure shows the distribution of the (log of the) value of relationships in the season 2006/2007. The value is given by the maximum temptation to deviate. The temptation to deviate is the value at the auctions of quantities traded in a relationship in a week. In a given season, the maximum temptation to deviate is given by the highest temptation to deviate during the season. Among the relationships in our baseline sample, those active immediately before the violence period, relationships that were already active before 2006/2007 are depicted with a solid line, new relationships with a dashed line, and relationships that were active in 2006/2007 but did not survive with a light gray line. The figure displays that relationships with higher values are more likely to survive. The equality of mean (and distribution) between surviving and dying relationships is rejected with 1 percent confidence interval. New relationships also have lower values. The equality of mean (and distribution) between new and established relationships is rejected with 1 percent confidence interval. For data sources, please refer to the online Appendix.

The former observation, however, cannot be interpreted as evidence that the value of a relationship increases with age. First, as the second fact suggests, there could be selection effects. Second, in a mechanical way the estimated value of a relationship that is too young to have gone through a seasonal peak is low. Third, the relationship between the two variables of interest could be non-monotonic, in which case Figure 7 would be misleading. We therefore turn to a formal econometric analysis.

Table 4 presents correlation patterns between relationship age and the main relationship outcomes. Equation (6) in the theory section shows that beliefs about the seller's type are an increasing and (eventually) concave function of the past number of shipments in the relationship. Accordingly, in panel A, we measure age of the relationship as the log of the number of past shipments and denote this variable as $\log(AGE_{sb})$ in cross-sectional specifications and $\log(AGE_{it})$ in the panel. For ease of interpretation, however, in panel B we also report specifications in which the age of the relationship is measured in level. Odd numbered columns in Table 4 report results that exploit cross-sectional variation in the season before the violence, i.e.,

$$\log(\hat{y}_{sb}) = \mu_s + \eta_b + \beta \log(AGE_{sb}) + \varepsilon_{sb}, \tag{11}$$

TABLE 4—AGE OF THE RELATIONSHIPS AND OUTCOMES (TEST 2)

	Trade volume		Relationship value		Buyer value		Seller value	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Age of the relationship (*log*)								
Age of the relationship	0.675***	0.561***	0.818***	0.617***	0.579***	0.542***	1.250***	0.746**
	(0.105)	(0.095)	(0.147)	(0.102)	(0.160)	(0.092)	(0.393)	(0.224)
Adjusted R^2	0.779	0.824	0.760	0.854	0.600	0.739	0.669	0.654
Panel B. Age of the relationship (*level*)								
Age of the relationship	0.198***		0.239***		0.163**		0.388***	
	(0.052)		(0.071)		(0.070)		(0.117)	
Adjusted R^2	0.741		0.708		0.562		0.660	
Seller and buyer fixed effects	Yes	—	Yes	—	Yes	—	Yes	—
Relationship fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Season fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	156	430	156	430	156	430	111	430

Notes: The table reports correlations between the relationship outcomes and the age of the relationship. The pure limited enforcement model predicts zero correlation between relationship outcomes and age of the relationship while the learning model predicts positive correlation (Test 2). Age of the relationship is measured as the number of previous shipment in the relationship. In panel A the age is in logs and in panel B it is in levels (hundreds of past transactions). The outcomes are computed for all seasons before the violence and the sample refers to relationships that were active during the period. The sample excludes relationships that are in the baseline sample but were not active in the season preceding the violence and includes relationships that did not survive until the violence season. Following business practices in the industry, a season starts in mid-August. The three considered seasons are those starting in August 2004, 2005, and 2006. Robust standard errors, clustered at the firm level are reported in parenthesis.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

where $\hat{y}_{sb}$ are the outcomes of interest, μ_s and η_b are seller and buyer fixed effects respectively and ε_{sb} is an error term. The regression is estimated on the sample of relationships that were active in the season before the violence.[27]

From a cross section it is not possible to disentangle age and cohort effects. The inclusion of buyer and seller fixed effects controls for cohort effects at the contractual-party level, but does not control for relationship cohort effects, the fact that more valuable relationships might have started earlier. Moreover, cross-sectional correlations could be driven by selection effects. Even numbered columns in Table 2, therefore, present results from an alternative specification that exploits the time variation across seasons. This allows us to include relationship fixed effects that control for time-invariant relationship characteristics, including cohort effects. With panel data, it is not possible to separately identify the linear effect of age, cohort, and season effects since cohort, age, and season effects are collinear. However, our measure of the age of the relationship in panel A, $\log(AGE_{it})$, is a non-linear function

[27] This specification adapts the ones in McMillan and Woodruff (1999) and Banerjee and Duflo (2000) to our environment.

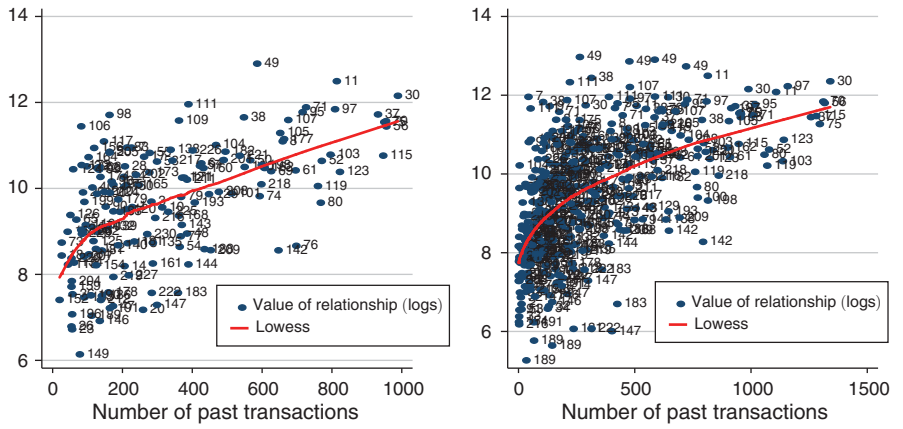

FIGURE 8. VALUE OF RELATIONSHIPS AND NUMBER OF PAST TRANSACTIONS

Notes: The figure illustrates non-parametrically the association between the (log) value and age of the relationship. The left panel depicts the raw observations in the cross-sectional specification used in column 3, Table 4. The right panel depicts the raw observations for the balanced panel specification in column 4, Table 4. For data sources, please refer to the online Appendix.

of calendar time and, therefore, allows us to include season fixed effects. The even columns in Table 4 (panel A only), report results from the following specification:

$$\log(\hat{y}_{it}) = \mu_i + \phi_t + \beta \log(AGE_{it}) + \varepsilon_{it}, \tag{12}$$

where μ_i are relationship fixed effects, ϕ_t season fixed effects, and ε_{it} is an error term. The selection effect documented in Figure 7 could induce a spurious positive correlation. The specification is therefore estimated on a balanced sample of relationships that were active in all three seasons prior to the violence.

Before presenting regression results, Figure 8 presents the data. The figure illustrates non-parametrically the association between the (log) value and age of the relationship in the cross-sectional sample (left panel) and in the balanced panel sample (right panel). In both cases, Figure 8 shows a strong positive association reasonably well approximated by an increasing and concave function. Results in Table 4 confirm a positive correlation between all relationship outcomes and age. Columns 1 and 2 report results for the quantity traded when the incentive constraint binds, $q^R_{i,t\omega^*_{it}}$. Columns 3 and 4 focus on the main outcome variable, the relationship's value $\hat{S}_{it}$. To understand how parties split the relationship's value over time, columns 5 and 6 consider the value of the relationship for the buyer and columns 7 and 8 for the seller. Regardless of whether cross-sectional or time variation is used, the age of the relationship positively correlates with all relationship's outcomes. Parties split the higher value of the relationship over time.

Table 5 explores the robustness of these results focusing on the two main outcomes of interest, $q^R_{i,t\omega^*_{it}}$ and $\hat{S}_{it}$. The positive correlation between relationship age and outcomes could be driven by changes in seasonality patterns. Columns 1 and 5 control for seasonality effects and find results to be robust. Results could also be sensitive to the choice of the length of the period to compute deviations. Columns 2 and 6 construct the outcome variables assuming a two week long deviation period

Table 5—Age of the Relationships and Outcomes (Test 2): Robustness Checks

	Trade volume				Relationship value			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age of the relationship	0.628***	0.654***	0.837***	0.485***	0.619***	0.685***	0.848***	0.544***
	(0.073)	(0.108)	(0.292)	(0.118)	(0.082)	(0.110)	(0.267)	(0.120)
Relationship fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Season fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonality fixed effects	Yes	No	No	No	Yes	No	No	No
Two weeks deviation window	No	Yes	No	No	No	Yes	No	No
Alternative age measure	No	No	Yes	No	No	No	Yes	No
Max. auction price experienced	No	No	No	Yes	No	No	No	Yes
Adjusted R^2	0.852	0.865	0.814	0.835	0.868	0.877	0.839	0.869
Observations	430	430	424	372	430	430	424	372

Notes: The table reports correlations between the relationship outcomes and the age of the relationship. The pure limited enforcement model predicts zero correlation between relationship outcomes and age of the relationship while the learning model predicts positive correlation (Test 2). Age of the relationship is measured as the number of previous shipment in the relationship. All variables are in logs. The outcomes are computed for all seasons before the violence and the sample refers to relationships that were active during the period. The sample excludes relationships that are in the baseline sample but were not active in the season preceding the violence and includes relationships that did not survive until the violence season. Following business practices in the industry, a season starts in mid-August. The three considered seasons are those starting in August 2004, 2005, and 2006. Seasonality fixed effects are dummies for the week of the season in which the maximum aggregate temptation to deviate occurs. Columns 2 and 6 compute relationship outcomes using two weeks deviations period. Columns 3 and 7 measure age as the (log of the) number of days since the first shipment in the relationship. Columns 4 and 8 control for the highest auction price ever experience by the relationship. Robust standard errors, clustered at the firm level are reported in parenthesis.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

and confirm the findings. The number of previous shipments confounds frequency of shipment and age of the relationship measured in calendar time. Columns 3 and 7 measure age as (the log of) the calendar time elapsed between the first shipment observed in the data and the time of the highest temptation to deviate in a given season. Again, results are robust. Finally, relationship outcomes might mechanically increase with time, as the highest auction price ever experienced by a relationship mechanically increases with time. Columns 4 and 8 control for the highest auction price ever experienced by the relationship and still find results to be robust.[28]

D. *Test 3: Reputational Forces at the Time of the Violence*

Reliability at the Time of the Violence.—The evidence in Tables 4 and 5 rejects the pure limited enforcement model and supports the predictions of the model with learning. Additional evidence shows that the aggregate incentive constraint (5) is binding for all relationships in the sample, from youngest to oldest. The evidence is

[28] Results are robust to a variety of different assumptions and specifications. In particular: (i) outcomes can be measured in levels, instead of logs; (ii) relationships for which estimated $\hat{V}_{it}$ are negative can also be included (assigning them a value of zero); and (iii) we do not find evidence of any difference between relationships in the conflict and no-conflict regions.

consistent with relationships converging to a constrained volume of trade as learning about the seller's type unfolds. The positive correlation between relationship's age and outcomes, however, could be driven by factors other than learning about the seller's type. This section provides further empirical tests of the model with learning by examining how relationships reacted to the violence. In particular, the model with learning about the seller's type predicts that the delivery of roses during the violence is an inverted-U shaped function of the age of the relationship (Test 3).

We begin by constructing a measure of reliability at the time of the violence. For simplicity, we measure reliability as the ratio between actual shipments volumes during the week of the violence divided by the average volume shipped in the relationship during the control period, i.e., the first 20 weeks of the season.[29] Denote by y_{sb} the observed shipments of roses in the relationship between seller s and buyer b during the week of the violence, and by y_{sb}^0 the average weekly shipment of roses in the same relationship during the control period. Reliability at the time of the violence is given by

$$\hat{\mathcal{R}}_{sb} = \frac{y_{sb}}{y_{sb}^0}. \tag{13}$$

The first two columns in Table 6 show that the violence reduced reliability $\hat{\mathcal{R}}_{sb}$. The first column in Table 6 simply compares reliability of relationships across the two regions. Reliability was approximately 17 percent lower in relationships in the conflict region. The second column in Table 6 includes additional controls. Specifically, column 2 reports results from the regression

$$\hat{\mathcal{R}}_{sb} = \alpha_b + \beta\left(\mathrm{I}_s^{C=1}\right) + \gamma \mathbf{Z}_{sb} + \eta \mathbf{X}_s + \varepsilon_{sb}, \tag{14}$$

in which $I_s^{C=1}$ is an indicator function that takes value equal to one if seller s is located in the region affected by the violence and zero otherwise; $\mathbf{Z}_{sb}$ is a vector of relationship controls, $\mathbf{X}_s$ is a vector of seller controls, and α_b are buyer fixed effects. Relationship controls are average price and volumes during the control period. Seller controls are size (in hectares of land under greenhouses), fair trade certification, age of the firm, membership in main business association and ownership dummies (foreign, domestic Indian, indigenous Kenyan). Note that the reliability measure $\hat{\mathcal{R}}_{sb}$ is a deviation from a relationships-specific counterfactual. The controls included in specification (14), then, allow the violence period to have affected export volumes in a particular relationship differentially across buyers, sellers, and relationship characteristics.[30] Column 2 confirms that the violence reduced reliability.

[29] In earlier versions, we exploited the regularity of shipments within relationships to construct a counterfactual measure of the volumes of roses that should have been delivered in a particular relationship had the violence not occurred. We separately estimated for each relationship a model predicting shipments of roses in a particular day based on previous week shipments, seasonality, and day of the week fixed effects. Results are virtually identical.

[30] The results from specification (14), therefore, are equivalent to those of a regression of volumes of exports $\tilde{y}_{sb\omega t}$ in week ω of season t, on relationship-specific seasonality and season fixed effects, $\mu_{sb\omega}$ and μ_{sbt}, in which the effects of the violence are recovered from an interaction between a dummy for the period of the violence, $v_{\omega t}$, and a dummy for the conflict region, c_s, after controlling for the interaction between $v_{\omega t}$ with seller and relationship characteristics and buyer fixed effects.

Table 6—Reliability at the Time of the Violence (Test 3)

	Dependent variable: reliability during violence			
Sample	All firms (1)	All firms (2)	Firms in no-conflict regions (3)	Firms in conflict regions (4)
Conflict region	−0.174***	−0.200*	—	—
	(0.031)	(0.115)		
Age of the relationship			−0.010	0.200**
			(0.040)	(0.104)
Age of the relationship (sqrd)			0.0001	−0.020***
			(0.004)	(0.009)
Relationship controls	No	Yes	Yes	Yes
Seller controls	No	Yes	—	—
Buyer fixed effects	No	No	Yes	Yes
Seller fixed effects	No	No	Yes	Yes
Adjusted R^2	0.093	0.027	0.100	0.396
Observations	189	189	189	189

Notes: The table reports differences in estimated reliability between direct relationships of firms located in regions directly affected by the violence against firms located in regions not directly affected. The learning model predicts an inverted-U shape relationship between reliability and age of the relationship (Test 3). Reliability is computed as the ratio between actual shipments volumes during the week of the violence divided by the average volume shipped in the relationship during the control period, i.e., the first 20 weeks of the season. Age of the relationship is measured as the number of previous shipments in the relationship (in hundreds of transactions). Robust standard errors, two-way clustered at the seller and buyer levels, are reported in parenthesis.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Reliability and Relationship's Age.—We now turn to Test 3: the predicted non-monotonic relationship between the age of the relationship and reliability. Recall the model points at two distinct mechanisms. The positive correlation between relationship age and value for the seller (empirically confirmed in columns 7 and 8 in Table 4) implies that sellers in older relationships have stronger incentives to exert effort during the violence and deliver roses to the buyers. At the same time, in very old relationships, little uncertainty is left regarding the seller's type. Low reliability, then, would not lead to overly pessimistic beliefs about the seller's type and to termination of the relationship. The model with learning about the seller's type, therefore, predicts an inverted-U relationship between reliability and relationship's age (Test 3).

Figure 9 illustrates the non-parametric relationship between reliability and relationship's age for the two separate samples of relationships in the conflict and in the no-conflict region. The figure shows an inverted-U shaped relationship between reliability and relationship's age in the conflict region. In contrast, there is no relationship in the no-conflict region. The figure, therefore, lends strong support to the predictions of the model. Columns 3 and 4 of Table 6 explore the relationship between reliability $\hat{\mathcal{R}}_{sb}$ and relationship's age more formally for the conflict and no-conflict regions separately. For each separate region, columns 3 and 4 estimate the following specification:

$$(15) \qquad \hat{\mathcal{R}}_{sb} = \alpha_b + \mu_s + \beta_1(AGE_{sb}) + \beta_2(AGE_{sb})^2 + \gamma \mathbf{Z}_{sb} + \varepsilon_{sb},$$

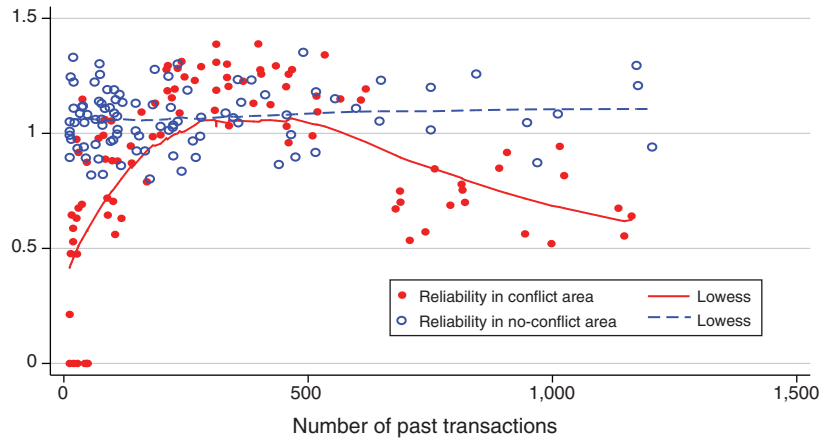

FIGURE 9. RELIABILITY AND CONFLICT IN DIRECT RELATIONSHIPS

Notes: The figure illustrates non-parametrically the association between reliability and the relationships age for the two separate samples of relationships in the conflict and no-conflict region. The figure depicts an inverted-U shaped association between reliability and relationships in the conflict region. In contrast, there is no such association in the no-conflict region. For data sources, please refer to the online Appendix.

where, as before, α_b are buyer fixed effects and $\mathbf{Z}_{sb}$ are relationship controls. The specification in (15) is very similar to the one in (14), but note that it now includes seller fixed effects μ_s. It is now possible to include seller fixed effects since we are interested in comparing relationships within firms. The age of the relationship AGE_{sb} is as before measured by the number of previous transactions (in hundreds) and is now included in levels rather than in logs to allow for a more transparent interpretation of the nonlinear pattern.[31]

The results confirm the findings in Figure 9: there is an inverted-U relationship between reliability and relationship's age in the conflict (column 3) but not in the no-conflict (column 4) region. To help with the interpretation of the results, note that the estimated coefficients imply that reliability at the time of the violence negatively correlates with relationship's age for relationships with age greater than $-\hat{\beta}_1/2\hat{\beta}_2 \simeq 0.2/(2 \times 0.02) = 5$. In the sample, this corresponds to approximately one quarter of relationships in the conflict region.[32]

E. *Effort at the Time of the Violence: Direct Evidence*

The evidence supports the predictions of the limited enforcement model with learning about the seller's type. The model predictions rest on the assumption that firms in the conflict region could have exerted costly and unobservable effort to

[31] Results are qualitatively unchanged if the log specification is used.

[32] Additional results are consistent with the logic of a model with learning about the seller's type. Since reliability is informative about the seller's type, the model also predicts that reliability correlates with subsequent outcomes in the relationships. We find that (i) more relationships did not survive to the following season in the conflict region (16 out of 94, i.e., 17 percent) than in the no-conflict region (8 out of 95, i.e., 8.5 percent); (ii) reliability positively correlates with relationships' survival in the conflict region but not in the no-conflict region; and (iii) in the conflict region reliability correlates with better outcomes in the subsequent season, but less so for older relationships.

FIGURE 10. PRICES AT AUCTIONS VERSUS DIRECT RELATIONSHIPS

Notes: The figure displays the distribution of average FOB price per stem in direct relationships at the time of the violence. The two vertical lines show the average prices of small and large stems of roses at the Dutch auctions at the time of the violence (the left most is the average auction price for small roses and the right most is for large roses). The figure illustrates that most relationships paid prices lower than at the spot market during violence. Further FOB prices in direct relationships in the conflict region were not renegotiated during the time of violence. The figure shows the distribution of average FOB prices per stem in direct relationships at the time of the violence and in the control period, i.e., the ten weeks prior to the violence. For data sources, please refer to the online Appendix.

protect deliveries to direct buyers. We conclude the empirical section providing direct evidence that firms exerted effort during the violence, as assumed in the model. Two margins of effort are considered: (i) reducing sales to the auctions, which was costly due to high prices paid on the spot market during the violence, and (ii) effort to keep workers coming at the farm to harvest during the violence.

Figure 10 shows that, at the time of the violence, prices in most direct relationships were lower than prices on the spot market. Table 7 shows that, despite higher prices at the auctions, export volumes to the auctions dropped significantly more than export volumes to direct buyers in the region affected by the violence. Column 1 extends the analysis of reliability in specification (14) to also include sales to the auctions.[33] Sales to the auctions were about 50 percent lower than normal times for firms in the conflict region. The drop in sales to the auctions for these firms was significantly larger than the drop in sales to direct relationships, which was only about 16 percent. No pattern is observed for firms in the no conflict region. Column 2 repeats the exercise controlling for seller fixed effects, i.e., comparing sales to the two channels within the same firm. The results are robust. Seller in the conflict region gave up profits from delivering to the auctions at higher prices to protect their direct relationships.

The remaining two columns of Table 7 focus on a second effort dimension: worker retention. Firms located in regions affected by the violence reported an average of 50 percent of their labor force missing during the period of the violence. Firms could try to retain workers and limit disruptions in harvesting by setting up camps on or

[33] Reliability at the auctions is computed as reliability in direct relationships.

TABLE 7—EFFORT AT THE TIME OF VIOLENCE: DIRECT EVIDENCE

	Reliability during violence		Percent workers lost	
Dependent variable	Relationships		Seller	
Sample	(1)	(2)	(3)	(4)
Conflict region	−0.595***	—	—	—
	(0.112)			
Direct relationship	−0.022	−0.043		
	(0.058)	(0.105)		
Direct relationship × conflict region	0.421***	0.479**		
	(0.117)	(0.194)		
Seller only sells to the auctions			16.783	40.157***
			(13.678)	(12.718)
Seller sells to both marketing channels			12.067	7.978
			(13.748)	(10.315)
Seller fixed effects	No	Yes	—	—
Location fixed effects	No	—	Yes	Yes
Seller controls	No	No	Yes	Yes
Only sellers in conflict region	No	No	Yes	Yes
Adjusted R^2	0.248	0.331	0.039	0.594
Observations	262	262	42	42

Notes: The table reports direct evidence that firms exerted effort to maintain deliveries to direct buyers. Column 1 expands the specification in column 2 of Table 6 including sales to the auctions during the violence. Reliability at the auctions is computed as reliability in direct relationships in Table 6. Firms in the conflict region had significantly lower exports than usual. The column documents a differential effect across the two marketing channels, with significantly lower export reductions to direct relationships. Column 2 includes seller fixed effects. Robust standard errors, clustered at the seller level, are reported in parenthesis in columns 1 and 2. Columns 3 and 4 report results at the seller level focusing on the sample of interviewed sellers located in the conflict region. Correlations between the percentage of workers reported missing during the violence and the marketing channels used by the firm are reported. Workers lost (percent) is the highest percentage reported by the firm throughout the period during and following the eruption of violence. These results also appear in Ksoll, Macchiavello, and Morjaria (2013). Robust standard errors, clustered at the location level, are reported in parenthesis.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

around the farm for workers threatened by the violence. Focusing on the conflict region alone, column 3 finds that firms that only sold to direct buyers in the period before the violence retained a higher percentage of workers than firms that specialized in selling to the auctions (not statistically significant). Column 4 shows that the correlation is statistically significant after controlling for characteristics of the firm's labor force (gender, ethnicity, contract type, and housing programs), firm characteristics (ownership type, certifications, and land size) and exposure to the violence, as proxied by location fixed effects. The evidence is consistent with firms trying to retain workers to guarantee deliveries to their direct buyers.

IV. Discussion

The evidence strongly supports the model with limited enforcement and learning about the seller's type: (i) due to limited enforcement, the volume of trade is constrained by the value of the relationship (Test 1); (ii) the value of the relationship increases with age (Test 2); and (iii) deliveries at the time of the violence are an inverted-U shaped function of the age of the relationship (Test 3), as predicted by

the model. Before concluding, this section discusses the role of unobserved rose characteristics, some key assumptions in our model, and how the evidence relates to alternative theoretical models.

A. *Unobserved Rose Characteristics*

The value of a rose mainly depends on (i) its size, which we proxy with unit weights reported in the customs data, and (ii) its variety which, unfortunately, is not reported. Unobserved rose characteristics present two main concerns for our results. A first concern regards the seller's incentive constraint (3) and its empirical implementation in (10). To estimate the lower bound to the value of the relationship we assumed that the roses can be sold at the auctions. A violation of the assumption introduces measurement error. The auctions are an extremely liquid market in which hundreds of rose varieties are traded each day. Conversations with practitioners suggest that the assumption is likely to be valid in most cases. Still, it is possible that for some relationships the assumption is violated. Three aspects of the empirical results are reassuring regarding the importance of this source of measurement error. First, Table A2 in online Appendix D shows that, within firms, there is no difference in the average and standard deviation of unit weights sold to direct buyers and to the auctions. Second, the predictions of the model hold for two outcome variables, quantities, and value of the relationship for the buyer, that do not directly depend on prices at the auctions. Third, the evidence of a binding incentive constraint (5) in Table 2 suggests that side-selling to the auction is the relevant deviation in most relationships.

A second concern is that firms might export to different buyers varieties of roses that are differentially affected by the violence (e.g., more labor intensive or perishable varieties). If those rose characteristics correlate with the age of the relationship, the results in Table 6 might be biased. Online Appendix Table A2 shows that average and standard deviation of unit weights do not correlate with the age of the relationship. Further (unreported) results show that average and standard deviation of unit weights do not change with season and at the time of the violence within relationships. To the extent that data allows, we do not find evidence that unobserved rose characteristics pose a threat to the results.

B. *Assumptions in the Model*

We assumed that prices are constant within seasons. The complexity associated with indexing contracts on weekly auction prices, the inability of sellers and courts to observe the quality of roses delivered and a desire to smooth seasonality in income profiles are likely forces behind the use of constant prices. We abstract from these forces and take constant prices as a fact of commercial life in our environment. The qualitative insights of the model are robust to allowing prices to change across seasons.

A second assumption is that outside options do not change over time. The assumption is justified by the fact that outside options are likely to be functions of seller's specific, rather than relationship's specific, variables that evolve over time. The empirical analysis controls for seller's fixed effects, effectively comparing relationships holding constant seller's specific factors that could determine outside options.

We have assumed that the violence was an unforeseen event and a corresponding plan of action was not specified in the original relational contract. This assumption simplifies the analysis and is in line with interviews in the field. We conjecture that a model in which the relational contract specifies a plan of action for the violence and the likelihood of violence tends to zero would generate qualitatively similar results.

C. *Informal Insurance*

Insurance considerations could also be important determinants of the value of relationships in this context.[34] Informal insurance models also predict non-stationary outcomes: past realizations of shocks influence future continuation values. Because past realization of shocks are unobservable it is difficult to reject informal insurance models. The results, however, suggest that insurance considerations are unlikely to be driving how relationships reacted to the violence. First, insurance models predict that relationships with higher promised value should give more slack to the seller. The evidence suggests the opposite is true: older, and more valuable, relationships tend to have higher reliability. Second, insurance considerations imply the use of both current transfers and future values to provide incentives. In contrast, the distribution of prices at the time of the violence is very similar to its counterpart in the 20 weeks before the violence. Prices were not renegotiated upward at the time of the violence (see Figure 10). The lack of price renegotiation is, however, consistent with the model. The binding incentive constraint (5) implies that during the violence buyers could not promise higher prices in case of delivery.

D. *Alternative Modeling Assumptions*

Levin (2003) extended the relational contracts literature (see, e.g., MacLeod and Malcomson 1989; Baker, Gibbons, and Murphy 1994; Baker, Gibbons, and Murphy 2002) to the case of moral hazard and adverse selection with i.i.d. types over time. Under both scenarios, provided that (i) parties are risk-neutral and have access to monetary transfers, and (ii) the buyer's actions are perfectly observable; the constrained optimal relational contract is stationary. The evidence, therefore, rejects extensions of the model entirely based on this type of asymmetric information.

Other modeling assumptions, however, imply non-stationary outcomes without assuming learning. When there is moral hazard and the buyer privately observes the quality of the roses delivered stationary contracts are no longer optimal. Levin (2003) and Fuchs (2007), however, show that the optimal contract is a termination contract in which trade between parties continues in a stationary fashion provided performance is above a certain threshold during a certain period of time. If performance falls below the threshold, the relationship ends. The evidence is, therefore, also inconsistent with this extension of the model.

We have introduced learning about the seller's type assuming symmetric information between the buyer and the seller (as in, e.g., Holmström 1999). This allows us to focus on the empirical implications of learning. Halac (2012) and Yang (2013)

[34] While seasonal fluctuations in market prices are predictable, buyers and sellers might be subject to idiosyncratic demand and supply shocks.

study relational contract models with asymmetric information over types and obtain non-stationary outcomes.[35]

V. Conclusion

Imperfect contract enforcement is a pervasive feature of real-life commercial transactions. In the absence of formal contract enforcement, trading parties rely on the future rents associated with long-term relationships to deter short-term opportunism and facilitate trade. Empirical evidence on the structure of informal arrangements in supply relationships between firms has the potential to identify salient microeconomic frictions in specific contexts and inform policy, particularly in a development context. This paper presents an empirical study of supply relationships in the Kenyan rose export sector, a context particularly well-suited to study informal relationships between firms.

We find evidence consistent with models in which sellers value acquiring and maintaining a reputation for reliability. From a policy perspective, it is important to know whether learning and reputation are important determinants of firms' success in export markets. Firms might have to operate at initial losses in order to acquire a good reputation. Furthermore, if reputation is an important determinant of contractual outcomes, prior beliefs about sellers affect buyers willingness to trade, at least for a while. This generates externalities across sellers and over time, justifying commonly observed institutions such as certifications, business associations, and subsidies to joint marketing activities.

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