Do Contracting Incentives Matter?

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ABSTRACT: Agency theory explanations for agricultural contract designs are often observationally equivalent to perfect information explanations. Further, in order to test properly the hypothesis that moral hazard is important one must first test and accept the hypothesis that agents respond to contract incentives. If agents do not respond to contract incentives, then it is unlikely that moral hazard is significant. Accordingly, we move beyond contract design and focus on whether or not we can reject the hypothesis that moral hazard is important by examining growers' responses to price incentives for processing tomato quality. We utilize a natural experiment. In our data set, growers deliver processing tomatoes under a price incentives contract and for a fixed price per ton. We compare the quality of the tomatoes delivered under the two arrangements. Our results suggest that growers indeed do respond to price incentives by improving tomato quality.

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Modern economics has developed a number of insights into the forces governing contractual relations. Until recently, moral hazard and adverse selection were not applied to agricultural production contracts in a rigorous way. (Recent exceptions include Tsoulouhas and Vukina (1999), Hueth and Ligon (1999) and Goodhue (in press).) While mechanism design has helped economists understand agricultural production contracts, it is difficult to determine if it is the appropriate tool. In particular, it is difficult to identify empirically whether there is an underlying moral hazard or adverse selection problem motivating contractual provisions. Competing explanations are often observationally equivalent in empirical analyses of agricultural production contracts (Goodhue 1999).

Tomato production contracts, commonly signed before planting, often include positive and negative monetary payments for delivering tomatoes with specified quality attributes. The processor may offer these quality payments for moral hazard reasons or for production cost reasons. First, as incentives, these payments reduce the scope of any grower moral hazard regarding tomato quality, and mechanism design may be used to model the consequences of this reasoning. The moral hazard may be due to unobservable actions that affect tomato quality, or may be due to the costliness of monitoring grower actions relative to offering incentives. Alternatively, these payment specifications could allow the processor to minimize his cost of producing a final product with specific attributes by paying growers for preferred raw tomato attributes. Finally, the processor would minimize his production costs through the use of these quality payments *even* if quality attributes were completely random (provided growers are not too risk averse). Hence, these three explanations are observationally equivalent in processing tomato contract design.[1]

In this analysis, we move beyond the observationally equivalent design of the contract and focus on whether or not we can reject the hypothesis that moral hazard is important by asking the

[1] Of course, the explanations are not mutually exclusive, and there are other possible explanations.

following question: Do growers respond to contractually-specified marginal quality payments? If growers do not respond to these incentives, it is unlikely that they are designed to deal with a moral hazard problem. A lack of grower response would suggest that there is no systemic component to variations in tomato quality, and the incentives are designed to minimize processor costs. On the other hand, if growers do respond to these payments, so that there is a systemic component to variations in tomato quality, then these payments may be called incentives, and further tests are necessary to determine the applicability of contract theory. This paper undertakes a first step toward determining whether contracts are influenced by asymmetric information considerations or not. We test whether or not growers respond to quality payments.

We utilize a natural experiment regarding growers' responses to payments based on processing tomato quality. In our data set, growers deliver processing tomatoes under a standard contract with quality payments, and outside the contract for a fixed price per ton. Quality payments clearly raise the marginal benefit of improving quality, so we predict that if there is a systemic component to tomato quality then quality will be higher under the incentive contracts. We compare the quality of the tomatoes delivered under the two arrangements. Our results suggest that growers indeed do respond to quality payments by improving tomato quality.

Our sample is particularly well-suited for testing our hypothesis. The sample size is quite large: over 33,000 observations. The sample is complete: it includes all tomatoes delivered to a given processor by a group of growers over a four-year period. The sample is multi-dimensional: there are a number of tomato attributes that processors value, some of which are less costly for growers to deliver than others are. These attributes and the grower decisions which influence them are discussed in section three.

Although our sample is fully inclusive, the structure of the tomato industry insulates our data from common incentive endogeneity problems. If there was a continuous contracting situation, we would expect to see the continuous evolution of contract terms and a large variety of contracts. In contrast, our contracts are identical for everyone contracting *in a given year.* Hence, we don't need to worry about contract choice concerns within out sample. Similarly, the bargaining convention for the industry (discussed in section two) guarantees that the processor must offer a contract to the growers each year on a take it or leave it basis, so that the simultaneity problem is subdued. We can isolate what growers do in response to the contracts, due to the sequencing and bargaining choices in the industry.

1. Processing Tomato Market

Processing tomatoes are an important crop in California. In 1995, processing tomatoes were the state's ninth largest crop, accounting for \$672 million of gross farm income. The tomato growing region extends from as far south as the Mexican border up to the northern Sacramento Valley (Johnston 1997). California farmers grow and harvest the tomatoes, which they sell to processing plants. Most of the state's processing tomatoes are made quickly into paste during the harvest season. The paste is stored for further processing (ketchup, tomato sauce, etc.) throughout the year.

Before tomatoes are accepted for delivery at the processing plant, they undergo a state-mandated grading process at a state inspection station. The state inspection stations grade all of the tomatoes based on seven categories: percentage of tomatoes with worm damage, the Agtron color score, percentage of tomatoes with mold damage (mold), percentage of green tomatoes (greens), percentage of material other than tomatoes (MOT), percentage of limited use tomatoes (LU), and the sugar content or net soluble solids (NTSS).[2] Loads with excessive mold, greens, limited use tomatoes, worms and material other than tomatoes are subject to weight deductions; that is, a ton of harvested tomatoes may be only 1800 pounds of delivered (price-eligible) tomatoes, if the quality is too low. Below specified quality thresholds, the processor may reject the load. A relatively small

[2] In contrast to government grading systems for other agricultural products, such as grains and beef, industry members, both processors and growers, are generally satisfied with the grading system. It measures relevant quality attributes in a reasonably accurate fashion.

sample (100 pounds) is used to grade the quality of the 20+ ton load. Starbird (1994) examines the effects of the combination of a maximum worm percentage threshold and sampling have on growers' pesticide use decisions. He finds that the sampling process induces growers to use more pesticides than they would if every tomato in a load was graded.

Over two-thirds of the state's tomato growers belong to the California Tomato Growers' Association (CTGA), which acts as a collective bargaining agent [3]. The CTGA negotiates contracts with each processor individually on behalf of the growers contracting with that processor. The negotiations determine a base price and any quality incentive payments. Many processors use incentive payments, for example, Campbell Soup Co., Morning Star Packing Co. and Stanislaus Food Products all negotiated quality payments for the 1999 season. The relative and absolute magnitudes differ across processors. Once the CTGA approves a contract, the processor is free to offer it to growers on a take it or leave it basis. The negotiated contract is effectively a minimum price contract; although the negotiated contract is not technically binding for producers who are not CTGA members, the processors are prohibited from offering a lower priced contract to non-members. (Anecdotally, processors do not choose to offer higher-priced contracts, although this would be permitted.) While the ex ante bargaining process may limit the appropriateness of contract theory for evaluating *contract design*, it does not distort the usefulness of examining *contract outcomes* to see if individual growers respond to contract provisions.

Most processing tomatoes are delivered under contract. Industry observers estimate that roughly ninety-eight percent of processed tomatoes are contracted, which is consistent with the division in our sample. The remaining two percent, however, are essential for the smooth functioning of the tomato marketing system. Once a processing plant begins operating for the season, it must maintain the flow of tomatoes. If an inadequate supply forces the plant to shut down, it is very costly to reopen, since the entire system must be resterilized. Processors purchase non-contract tomatoes in

[3] Joanne Hancock, CTGA, personal communication, October 21, 1999.

order to ensure a smooth flow of inputs. These non-contract tomatoes are purchased by processors according to posted prices. While processors determine these prices, the market does not function as a true spot market, since posted prices remain constant for a number of weeks and do not reflect the marginal value of the tomatoes to the processor.

2. Tomato Production and Harvesting Process

Growers and processors typically sign contracts in January. The contracts specify the number of tons of processing tomatoes the grower is expected to deliver during each week of the harvest season. In addition to specifying the deliverable tons, the contract specifies fields and acres assigned by the grower for these deliveries. Allocated acreage is generally sufficient to meet the contract in the event of lower than average yields. This suggests another possible explanation for quality differences between contracted and noncontracted tomatoes: that quality is purely random, and rational growers allocate their higher quality tomatoes to satify their contract delivery requirements and receive the price premiums.[4] This explanation seems inconsistent, however, with accepted tomato industry practices. Processors will often accomodate extra tons from growers under the provisions of the contract, including the quality payments. Anecdotally, growers sometimes plant tomato acres for which they do not have a contract. Further, this explanation can not fully explain the delivery pattern in our data. Only two percent of all loads in our sample were not delivered under contract, which can not account for all of the additional tomatoes produced when yields are high. In some cases, growers deliver contracted and non-contracted tomatoes in different weeks, which indicates that substitutability is limited. Similarly, the tomatoes may be different varieties, which again indicates limited substitutability.

Once the contract has been signed, the grower and the processor's field staff work together to set the grower's planting schedule and choose the tomato varieties the grower will plant (See Table

[4] We are indebted to Richard Sexton for suggesting this possibility.

1). The choice of tomato variety is the largest determinant of final sugar content (NTSS), and also affects the share of limited use tomatoes (LU) and underripe tomatoes (Greens).

Once the tomatoes are planted, the grower chooses his fertilizer and water regime. If the grower wants to increase NTSS for a given variety, the grower can stress the plants by withholding fertilizer and water. However, the increase in NTSS comes at the expense of yield, so high NTSS is the most expensive quality for the grower to deliver. The grower applies pesticides as necessary, subject to processor approval.

Weather, especially rain and average daily temperatures, affects tomato quality. Ordinarily, rain is a potential problem only for tomatoes harvested in the latter part of September or in October. If there are heavy rains, the tomatoes will be susceptible to mold damage and the grower may lose his entire tomato crop. Temperature affects tomato color and the share of LU tomatoes. The tomatoes need a certain number of heat units to ripen and achieve a good color score. Once ripe, tomatoes are still affected by heat units. High temperatures near harvest can increase the share of limited use tomatoes. This effect is intensified by high temperatures at the time of harvest.

The grower and the processor's field staff decide jointly when to harvest. The timing of this decision is critical to both parties. The processor's field staff is primarily concerned with managing the flow of tomatoes to the processor. They are also concerned with helping the grower deliver the best possible quality. About 18-20 days before the harvest, when 30% of the tomatoes are ripe, the grower may choose to apply ethephon to speed the ripening of the tomatoes. Ethephon is most commonly used early in the season and late in the season when cooler temperatures slow ripening. A highly skilled grower will time the harvest to maximize the share of ripe tomatoes and minimize the share of LU tomatoes: the rule of thumb is to harvest when 95% of the tomatoes are ripe. Harvesting too early can reduce NTSS and increase greens. As the tomatoes ripen, controlling the share of LU tomatoes becomes a bigger concern. For instance, the grower may choose to harvest at night when it is cooler. The harvest window for very high quality tomatoes varys greatly between tomato varieties, but it can be as long as 2-3 days and using ethephon narrows this harvest window. The harvest window for acceptable quality is much longer, and even lasts 10 days for some varieties.

The grower's sorting decisions during harvest affects the share of LU, Mold, Greens and MOT. If the grower mistimes the harvest, i.e. harvests too late when there is a large share of LU, or too early when there is a large share of Greens, the grower can still deliver high quality by increasing sorting effort. First, the grower sets the sensitivity level of the mechanical sorter which is particularly effective at removing green tomatoes and MOT. However, it is possible for the mechanical sorter to be too sensitive, so that it will reject too many good tomatoes. Second, the grower chooses how many workers ride the harvester and remove LU, Mold, Greens and MOT. More workers increases sorting effectiveness but also increases labor costs. Finally, the farmer chooses the speed of the tomato harvester. The workers can sort more effectively when the harvester is moving slowly, but again labor costs increase.

Given the composition of tomatoes in the field, Greens and MOT are the least expensive qualities to deliver since the grower merely has to increase the sensitivity of the mechanical sorter on the tomato harvester. LU and Mold require more sorting effort and so are more expensive qualities to deliver. The most expensive quality to deliver is NTSS, due to the yield tradeoff.

3. Theoretical Model and Testable Hypotheses

We develop a simple theoretical model that predicts how growers will respond to quality incentives. We assume for analytical convenience that growers are risk-neutral. We first briefly consider the case where tomato quality is purely exogenous to growers' decisions before examining the case where grower actions affect tomato quality. If growers are risk-neutral and quality is unaffected by grower decisions or actions or indirectly though the effects of these decisions on output, then risk-neutral growers will not alter their production decisions in response to a change in quality incentives. Since their production decisions are unaltered, we would not expect to see the quality of their delivered output affected. There is certainly an element of randomness in tomato quality and quantity, due to the effects of weather, however, we hypothesize that these are not the only effects. We test for evidence of systemic effects on tomato production due to grower actions.

Our risk neutral tomato producers maximize profits per acre. Each producer's total revenues are a function of the base price, the quality price incentives he faces, the weight deductions he faces, the tons of tomatoes he delivers and the quality of the delivered tomatoes. His total costs are a function of the tons of tomatoes he produces and the quality of his delivered tomatoes. His maximization problem over the quantity and quality of tomatoes he delivers may be written as follows:

$$\max_{q,Q} \quad Q(1-w(q))(B+p(q)) - C(Q,q) \tag{1}$$

where q is quality, Q is quantity, $w(q)$ is the weight deduction schedule, B is the base price per ton, $p(q)$ is the price premium schedule, and $C(Q,q)$ is the cost function. For the component functions $w_q < 0$, $w_{qq} < 0$, $p_q > 0$, $p_{qq} = 0$, $C_Q > 0$, $C_{QQ} = 0$, $C_q > 0$, $C_{qq} > 0$, and $C_{Q,q} > 0$.[5] This system is a simplification of the actual tomato price-quality relationship. The actual schedule includes minimum quality levels that must be met in order for the processor to accept the tomatoes. The derivatives over the choice variables are

$$(1-w(q))(B+p(q)) - C_Q = 0 \tag{2}$$

$$-Qw_q(B+p(q)) + p_q Q(1-w(q)) - C_q = 0 \tag{3}$$

[5] The two assumptions $p_{qq} = 0$ and $C_{QQ} = 0$ do not change the qualitative nature of our comparative statics results relative to the more general cases $p_{qq} > 0$ and $C_{QQ} > 0$. If instead of $C_{Q,q} > 0$ we assumed $C_{Q,q} \leq 0$, our results would only be strengthened.

The first order conditions determine the equilibrium levels of q and Q for the grower. Totally differentiating the first-order conditions, we obtain

$$0dQ + (-w_q(B+p(q)) + p_q(1-w(q)) - C_{Q,q})dq + (1-w(q))dB = 0 \tag{4}$$

$$(p_q(1-w(q)) - w_q(B+p(q)) - C_{Q,q})dQ - (Qw_{qq}(B+p(q)) + 2Qp_qw_q + C_{qq})dq - Qw_qdB = 0 \tag{5}$$

We can rewrite the system in matrix form as

$$\begin{vmatrix} 0 & -w_q(B+p(q)) + p_q(1-w(q)) - C_{Q,q} \\ p_q(1-w(q)) - w_q(B+p(q)) - C_{Q,q} & -Qw_{qq}(B+p(q)) - 2Qp_qw_q - C_{qq} \end{vmatrix} \begin{vmatrix} dQ \\ dq \end{vmatrix} = \begin{vmatrix} w(q)-1 \\ Qw_q \end{vmatrix} dB$$

Applying Cramer's Rule we obtain the effects of a change in the base price on the grower's choice of quality and quantity of production. For the determinant we have

$$\begin{aligned} DET = & -(-w_q(B+p(q)) + p_q(1-w(q)) - C_{Q,q})(p_q(1-w(q)) - w_q(B+p(q)) - C_{Q,q}) \quad (6) \\ = & -(-w_q(B+p(q)) + p_q(1-w(q)) - C_{Q,q})^2 \\ < & \ 0 \end{aligned}$$

Thus the effect of a change in the base price per quality-adjusted ton, B, on the grower's optimal choice of quantity (yield) and tomato quality is

$$\frac{dq}{dB} = -\frac{(1-w(q))}{-w_q(B+p(q)) + p_q(1-w(q)) - C_{Q,q}} < 0 \tag{7}$$

$$\frac{dQ}{dB} = \frac{(1-w(q))(-Qw_{qq}(B+p(q)) - 2Qp_q w_q - C_{qq}) + Qw_q(-w_q(B+p(q)) + p_q(1-w(q)) - C_{Q,q})}{DET}$$

$$= \frac{(w(q)-1)(Qw_{qq}(B+p(q)) + 2Qp_q w_q + C_{qq})}{DET} + \frac{-Qw_q}{-w_q(B+p(q)) + p_q(1-w(q)) - C_{Q,q}} \tag{8}$$

$$> 0$$

Both of these qualitative effects require $-w_q(B+p(q)) + p_q(1-w(q)) - C_{Q,q} > 0$. This condition implies that a change in the marginal benefit of q (Q) due to a change in Q (q) is larger than the change in marginal cost. Provided that the condition is met, an increase in the base price of tomatoes will increase the optimal quantity of tomatoes and reduce the optimal quality. Our data set contains an even more intuitive natural experiment. Growers deliver tomatoes under the standard contract with the associated quality premiums, and deliver tomatoes for a flat price with no quality *price* adjustments. (These fixed price deliveries are subject to the same schedule of quality-based weight deductions as tomatoes delivered under contract.) Clearly, eliminating the price incentives for increased quality reduces the marginal benefits to a grower of increasing tomato quality and leaves the cost function unaffected. Consequently, we would expect tomatoes delivered for a fixed price to be of lower quality than tomatoes delivered under a contract with price incentives for quality. The effects on output are less clear, since eliminating the price incentives affects both its marginal benefit and marginal cost.

4. Data

Our data set contains quality information on all the tomatoes delivered to one processing plant by a set of growers. All of the growers in the data set delivered tomatoes both under a standard incentive contract with price rewards and punishments for quality incentives, and under a nonstandard contract, with a fixed price. Tomatoes delivered under both types of contracts were subject to quantity adjustments for quality problems, according to the standard schedule used in the industry. Tomatoes delivered in contractually-indicated, year-specific weeks *under the standard incentive contract* received a late season bonus worth 10-30% of the base price per quality-adjusted ton. The data covers four years of tomato deliveries, from 1994-1997, on a load basis, for a total of 33001 loads delivered by 15 growers. For each load of tomatoes, the data set contains information on the quality attributes listed above, the date and time of harvest, the tomato variety, a grower identification number, and whether the load was delivered under a standard incentive contract or a nonstandard fixed price contract. Unfortunately, our data set does not contain any information on acres harvested or yield, so we can not test any quantity response predictions.

For confidentiality reasons, we do not report specific values of marginal quality incentives or base prices in specific years. Overall, the price incentives account for roughly 5% of the price per ton for a representative ton of tomatoes. While this may not seem to be a significant percentage, this margin is important, given costs and returns in the processing tomato industry. In 1997, for example, a producer with the state average yield per acre who incurred the costs estimated in the 1997 UC Extension Yolo County processing tomato budget and who received the base price from our data sample would have essentially zero profits. Thus, his performance on the quality incentives would determine whether he made a profit or a loss.[6]

Data are available on seven quality attributes graded by the state inspection stations: percentage of tomatoes with mold damage (mold), percentage of green tomatoes (greens), percentage of material other than tomatoes (MOT), percentage of limited use tomatoes (LU), and the sugar content or net soluble solids (NTSS). We ignore the worm damage category because less than one percent of the loads contained worm damage. We ignore the color score because the incentive contracts do not specify marginal incentives related to color and there are no weight adjustments for color. Furthermore tomato loads are never rejected due to color because the processor is able to either

[6] These crop budgets are controversial in the industry due to the high per acre overhead costs they assign. When these costs are excluded from this calculation the grower would net over $300 per acre before incentives.

mix tomato loads to achieve a good color or if the paste turns out to have poor color, the processor can blend it with other paste to achieve an acceptable color.

5. Empirical Model

Profit-maximizing growers equalize the price per delivered ton with the marginal cost of producing tomatoes with the requisite quality. Different tomato quality attributes are affected by different production decisions, and the attributes vary in their costliness of production. The grower's decision is described by a set of five equations, one for each quality variable. These equations are in reduced form. We do not explicitly model cross-effects among the variables.

NTSS is determined by the tomato variety, weather, time of season and grower practices. Sugar content varies greatly across tomato varieties so we include tomato variety dummy variables to control for these effects. The sugar content of tomatoes tends to increase over the course of the season and is affected by average daily temperatures. We include week-year dummies to control for these effects. The standard contract late season variable may capture weather effects, however, it will also capture the effect of the late season premium, which will tend to decrease NTSS, so that the net effect is indeterminate. Since the growers in our sample are located throughout inland central California, from the southern end of the San Joaquin Valley to the southern quarter of the Sacramento Valley, we include grower dummy variables and grower-variety interaction variables to account for soil and microclimate effects. The grower dummy will also reflect any differences in grower management ability that affect tomato quality. In the full sample regressions we include dummy variables for the year to control for large scale weather differences such as a cool spring that delays the start of the processing season. The year dummy variables will also capture the small changes in the marginal contract incentives across years.

Increasing NTSS comes at the expense of yield, making NTSS the most expensive quality to deliver.[7] If the standard contract incentives are sufficiently large we expect that grower effort will increase NTSS. Thus, we expect a negative coefficient on the dummy variable for the nonstandard contract. Accordingly, we specify the following equation:

$$\mathbf{NTSS} = \beta_1 + \underbrace{\beta_{\mathrm{NSC}}}_{-}\mathrm{NSC} + \underbrace{\beta_{\mathrm{SLATE}}}_{\text{indet.}}\mathrm{SLATE} + \beta_V V_i + \beta_{WY} WY_j + \beta_g g_k + \beta_{gV} gV_{k,i} + \epsilon_{\mathbf{NTSS}} \qquad (9)$$

where β_1 is the intercept, NSC is the dummy variable for a non-standard contract, SLATE is the dummy variable for a standard contract load eligible for the late season premium, V_i denotes the variety dummy variable for the ith variety, WY_j denotes the dummy variable for the jth week-year period, g_k denotes the dummy variable for the kth grower, and $gV_{k,i}$ denotes the dummy variable for the interaction between the kth grower and the ith variety. $\epsilon_{\mathbf{NTSS}}$ is the error term for the equation. Predicted signs are indicated below the coefficients, where appropriate.

The share of limited use (LU) tomatoes depends on grower skill and weather. Hotter weather at harvest-time tends to increase the share of limited use tomatoes. We include week-year dummy variables to account for these weather effects. We include grower, variety and grower-variety dummy variables for reasons similar to those given above: microclimate, soil, innate ability, variety differences, etc. We expect to see the share of LU tomatoes to decrease when the grower harvests at night and when the grower is rewarded for reduced LU with standard contract incentives. Thus, we predict a negative coefficient on the night harvest variable and a positive coefficient on the non-standard contract variable. The late season premium will reduce the grower's incentive to improve quality, so we would expect a positive coefficient on the standard contract late season variable. Thus, the estimated equation for (9) is

$$\mathbf{LU} = \beta_2 + \underbrace{\beta_{\mathrm{NSC}}}_{+}\mathrm{NSC} + \underbrace{\beta_{\mathrm{SLATE}}}_{+}\mathrm{SLATE} + \underbrace{\beta_{\mathrm{NIGHT}}}_{-}\mathrm{NIGHT} + \beta_V V_i + \beta_{WY} WY_j + \beta_g g_k + \beta_{gV} gV_{k,i} + \epsilon_{\mathbf{LU}} \qquad (10)$$

[7] Unfortunately, due to the lack of yield data we can not directly include this consideration.

where β_2 is the intercept, NIGHT is the dummy variable for harvesting at night, and the other dummy variables are as previously described. $\epsilon_{\mathbf{LU}}$ is the error term for the equation.

Mold damage occurs after heavy rains and we include week-year dummies to account for these weather effects. As in the previous equations, we include grower, and grower-variety dummy variables.

The grower can influence the percentage of mold through his harvest decisions. The grower may be able to harvest early, before the mold damage is severe but harvesting early generally implies a higher percentage of green tomatoes and a lower sugar content, which both reduce payments. As with LU tomatoes, the mechanical sorter is not very effective at removing moldy tomatoes, so that it can be very costly to deliver a load of tomatoes with little mold damage. We expect the coefficient on the standard contract late season variable to be positive due to both weather reasons and incentive reasons, since the late season premium reduces the incentive to improve quality. We predict that the coefficient on the nonstandard contract variable will be positive, for similar reasons as those discussed above. We specify the following equation, where β_3 is the intercept and $\epsilon_{\mathbf{Mold}}$ is the error term:

$$\mathbf{Mold} = \beta_3 + \underbrace{\beta_{\text{NSC}}}_{+}\text{NSC} + \underbrace{\beta_{\text{SLATE}}}_{+}\text{SLATE} + \beta_{WY}WY_j + \beta_g g_k + \beta_{gV} gV_{k,i} + \epsilon_{\mathbf{Mold}} \tag{11}$$

The cheapest tomato qualities to deliver are the percentage of greens and MOT. The mechanical sorter is very effective at removing green tomatoes and MOT. We expect to see greens and MOT decrease with the grower's sorting effort, when the grower is rewarded by standard contract incentives. As a result, positive coefficients on the nonstandard contract and standard contract late season variables are expected. Thus the following equation, where β_5 is the intercept and $\epsilon_{\mathbf{MOT}}$ is the error term, specifies (11) appropriately:

$$\textbf{MOT} = \beta_5 + \underbrace{\beta_{\text{NSC}}}_{+}\text{NSC} + \underbrace{\beta_{\text{SLATE}}}_{+}\text{SLATE} + \beta_g g_k + \epsilon_{\textbf{MOT}} \tag{12}$$

In addition to grower sorting effort, the percentage of greens can also be affected by the tomato variety and weather effects. The following equation, where β_4 is the intercept and $\epsilon_{\textbf{Greens}}$ is the error term explains the percentage of greens:

$$\textbf{Greens} = \beta_4 + \underbrace{\beta_{\text{NSC}}}_{+}\text{NSC} + \underbrace{\beta_{\text{SLATE}}}_{+}\text{SLATE} + \beta_V V_i + \beta_{WY} WY_j + \beta_g g_k + \beta_{gV} gV_{k,i} + \epsilon_{\textbf{Greens}} \tag{13}$$

6. Results

We tested the predictions above for the entire data set, 1994-1997, and separately for 1996 when 38% of the non-standard contract tomatoes were delivered. Testing a subsample for a single year allows us to control for small changes across years in the relative magnitude of the contract payments for the different quality attributes. It provides a more consistent set of biological factors and weather conditions. Applying ordinary least squares by equation results in a failed White's test for heteroskedasticity for both the full sample and subsample. Thus we report least squares regressions by equation with White's corrected standard errors. The processing tomato production process suggests that quality errors may be correlated across attributes. Hence, we also ran a seemingly unrelated regression, to correct for any such effects. Under both specifications for the full sample and the 1996 subsample, the results were consistent for ordinary least squares using White's correction for heteroskedasticity and using seemingly unrelated regressions. Quantitatively, results for a sample were not substantially affected by the model specification. Qualitatively, results were similar across samples. This consistency was likely due to the large sample sizes. Overall, the results indicate that growers do respond to quality incentives. Non-standard contract tomatoes are of lower quality than standard contract tomatoes. Results from the 1996 subsample support the hypothesis slightly more strongly than do results from the entire sample.

NTSS: For the equation with NTSS as the dependent variable, the coefficient on NSC was positive and significant for the full four-year sample. This not only contradicts our null hypothesis but it is counterintuitive because it implies that growers deliver higher quality without incentives. Recall, however, that in our development of our empirical model the predicted sign on SLATE was indeterminant, due to the opposing influence of biological factors. Hence, this result suggests that biological factors dominate contractual incentives: NTSS increases later in the season. While not all non-standard contract tomatoes were in the official late season window, they were mostly delivered in the latter two-thirds of the harvest season. This explanation is further supported by the positive and significant coefficient for standard contract late season tomatoes.

In the 1996 only regression, in contrast, the coefficient on the nonstandard contract loads was negative and significant. In this year, contractual incentives dominated biological factors. This finding makes sense intuitively, since biological considerations are more consistent across tomato loads within a given year, while contractual incentives still vary. The dummy on the standard contract, late season loads was negative and significant which implies that the late season premium reduced the quality of the tomatoes, as predicted.

LU: The coefficient on the non-standard contract dummy was positive and significant for all samples and specifications; non-standard loads statistically have a larger share of LU tomatoes. For LU, we reject the null hypothesis that growers do not respond to contract incentives. The coefficient on the standard contract, late season dummy was positive in all the regressions, but was significant only in the 1996 only regressions. The sign is consistent with the hypothesis that the late season premium reduces the impact of other contract incentives on the grower behavior. The coefficient on the dummy variable for harvesting at night was negative and significant which is consistent with the expectation that LU decreases with cooler temperature.

Mold: With mold as the dependent variable, the coefficient on NSC was positive and significant for all four regressions. For mold, we reject the null that growers do not respond to the contract incentives. The coefficient for the standard contract, late season tomatoes was positive, large and significant, which is consistent with both incentive and weather explanations.

MOT: For the equation with MOT as the dependent variable, the coefficient on NSC was positive and significant. Hence for MOT we reject the null hypothesis in favor of the alternative that growers do indeed respond to the standard contract incentives. The standard contract, late season dummy also had a positive, significant coefficient which which is consistent with our hypothesis that the late season premium may reduce the impact of the contract incentives on the grower's decisions.

For the 1996 data, the coefficient on NSC is still positive as expected although it is significant at the 1% level only in the SUR regression and is not significant in the corrected OLS regression. The coefficient on SLATE is negative and significant in both regressions, although it is significant at the 1% level only in the SUR regression. The sign on the SLATE coefficient is the opposite of the sign for the sample as a whole, and contradicts our hypothesis that the late season premium will be associated with higher levels of MOT.

Greens: For the 1996 data, the coefficients on the nonstandard contract dummy and the standard contract, late season dummy are positive, as predicted, and significant. For the full sample regressions with Greens as the dependent variable, the coefficients on NSC and Slate were positive but insignificant. In part, this may be due to the nature of the price incentives for this variable, which are second-order relative to the price incentives for the other quality attributes.

7. Conclusion

We utilize data on tomatoes delivered under a price incentive contract and a fixed price to examine if growers respond to quality payments. Overall, our results are consistent with the hypothesis that growers respond by increasing tomato quality. Hence, we can regard these payments as incentives. Both the nonstandard contract variable and the standard contract late season coefficients had the predicted sign in the regressions for limited use tomatoes, mold, greens and material other than tomatoes. Since the late season premium effectively increases the base price, it has a negative effect on quality. Nonstandard contracts had no price incentives for quality, so this variable had a negative effect on quality. All the coefficients were significant except for the limited use tomato nonstandard contract coefficient in the full sample regressions, both coefficients in the full sample greens regressions, and the nonstandard contract coefficient in the corrected OLS regression for 1996.

Results for net soluble solids were less conclusive. In the equation for net soluble solids (NTSS), both coefficients were positive and were significant in the regressions for the full sample, indicating that for this particular attribute biological considerations dominated incentive considerations. For the 1996 subsample, both coefficients were negative and significant, indicating that in that year incentive considerations dominated biological considerations. The mixed results for NTSS are not overly suprising, since NTSS is a very costly attribute for growers to deliver. Further, increasing NTSS reduces yield. Since we have no yield information, our analysis does not fully reflect growers' cost of increasing NTSS.

This analysis is an initial step toward determining whether tomato production contracts address problems due to asymmetric information, or simply seek to minimize production costs under symmetric information. If growers did not respond to the contract incentives, we could have rejected the hypothesis that moral hazard was an important consideration. However, growers did respond to contractual incentives. While our natural experiment allowed us to test grower response, further research is required to determine whether agency theory is an appropriate way to model these contracts. Evidence of grower response is not sufficient to identify an asymmetric information problem.

Table 6: Stylized Tomato Production and Harvesting Process

STAGES	DECISION MAKER	QUALITY AFFECTED
Pre-Planting		
Set Planting Schedule	Grower and Processor	
Choose Tomato Varieties	Grower and Processor	NTSS, LU, Greens
Production		
Fertilizer/Water Regime	Grower	NTSS
Pesticide Applications	Grower with Processor approval	
Weather		
Rain		Mold
Heat		LU, Color
Harvest		
Time of Harvest	Grower and Processor	NTSS, LU, Greens, Color
Sorting		
Mechanical	Grower	LU, Greens, Mold, MOT
No. of Workers	Grower	LU, Greens, Mold, MOT
Speed of Harvester	Grower	LU, Greens, Mold, MOT

Table 1: Dependent Variable NTSS: Selected estimated coefficients [a]

Variable (S.E.)	Full Sample Corrected OLS	SUR	1996 only Corrected OLS	SUR
Intercept	4.9397**	4.9541**	4.8208**	4.837554**
	(0.040759)	(0.051682)	(0.21393)	(0.38789)
NSC	0.15710**	0.15682**	-0.37036**	-0.356402**
	(0.027028)	(0.028887)	(0.074713)	(0.11466)
SLATE	0.086883**	0.085143**	-0.41551**	-0.400638**
	(0.030360)	(0.03004)	(0.076318)	(0.11537)

[a] ** significant at 1% level. * significant at 10% level. Regression information for full sample OLS regression with White-corrected standard errors:R^2= 0.3201; Adjusted R^2 = 0.3157; Estimated variance (σ^2) = 0.15383; Sum of squared errors (SSE)= 5043.4; Mean of the dependent variable = 5.0939; Log of the likelihood function = -15830.9. Regression information for the full sample SUR regression: System weighted MSE 1 with 164154 degrees of freedom; System weighted R^2: 0.2718. Regression information for 1996 OLS regression with White-corrected standard errors: R^2= 0.4169; Adjusted R^2 = 0.4111; Estimated variance (σ^2) = 0.13561; Sum of squared errors (SSE)= 1234.9; Mean of the dependent variable = 5.1171; Log of the likelihood function = -3816.64. Regression information for 1996 SUR regression: System weighted MSE: 1 with 45624; System weighted R^2: 0.3204.

Table 2: Dependent Variable LU: Selected estimated coefficients [a]

Variable (S.E.)	Full Sample Corrected OLS	SUR	1996 only Corrected OLS	SUR
Intercept	1.3817**	1.361763**	-2.3515**	-2.375232*
	(0.14224)	(0.185686)	(0.57691)	(1.367270)
NSC	0.27189**	0.271562**	3.0644**	3.045142**
	(0.085705)	(0.103452)	(0.34475)	(0.403182)
SLATE	0.070419	0.074962	2.6768**	2.656300**
	(0.088603)	(0.107589)	(0.34040)	(0.405661)
NIT	-0.33725**	-0.347714**	-0.28143**	-0.281277**
	(0.016758)	(0.016475)	(0.031129)	(0.029776)

[a] ** significant at 1% level. * significant at 10% level. Regression information for full sample OLS regression with White-corrected standard errors:R^2= 0.2674; Adjusted R^2 = 0.2626; Estimated variance (σ^2) = 1.9727; Sum of squared errors (SSE)= 64674.; Mean of the dependent variable = 1.6515 ; Log of the likelihood function = -57928.4 Regression information for the full sample SUR regression: System weighted MSE 1 with 164154 degrees of freedom; System weighted R^2: 0.2718. Regression information for 1996 OLS regression with White-corrected standard errors: R^2= 0.3311; Adjusted R^2 = 0.3244; Estimated variance (σ^2) = 1.6737; Sum of squared errors (SSE)= 15239; Mean of the dependent variable = 1.4007; Log of the likelihood function = -15373.4. Regression information for 1996 OLS regression with White-corrected standard errors: R^2= 0.4169; Adjusted R^2 = 0.4111; Estimated variance (σ^2) = 0.13561; Sum of squared errors (SSE)= 1234.9; Mean of the dependent variable = 5.1171; Log of the likelihood function = -3816.64. Regression information for 1996 SUR regression: System weighted MSE: 1 with 45624; System weighted R^2: 0.3204.

Table 3: Dependent Variable Mold: Selected estimated coefficients [a]

Variable (S.E.)	Full Sample Corrected OLS	SUR	1996 only Corrected OLS	SUR
Intercept	-0.47723**	-0.477127**	-0.30864	-0.299941
	(0.12541)	(0.114612)	(0.25025)	(0.241123)
NSC	0.29537**	0.294518**	1.0481**	1.035145**
	(0.079498)	(0.073877)	(0.25363)	(0.240039)
SLATE	0.55895**	0.559330**	1.0773**	1.062906**
	(0.074660)	(0.076574)	(0.25400)	(0.242669)

[a] ** significant at 1% level. * significant at 10% level. Regression information for full sample OLS regression with White-corrected standard errors: R^2= 0.3595; Adjusted R^2 = 0.3559; Estimated variance (σ^2) =1.0194; Sum of squared errors (SSE)= 33450.; Mean of the dependent variable = 1.3069; Log of the likelihood function = -47049.6. Regression information for the full sample SUR regression: System weighted MSE 1 with 164154 degrees of freedom; System weighted R^2: 0.2718. Regression information for OLS regression with White-corrected standard errors: R^2= 0.3913; Adjusted R^2 = 0.3864; Estimated variance (σ^2) = 0.79665; Sum of squared errors (SSE)= 7268.6; Mean of the dependent variable = 1.3525; Log of the likelihood function = -11968.7. Regression information for 1996 SUR regression: System weighted MSE: 1 with 45624; System weighted R^2: 0.3204

Table 4: Dependent Variable MOT: Selected estimated coefficients [a]

Variable (S.E.)	Full Sample Corrected OLS	SUR	1996 only Corrected OLS	SUR
Intercept	0.20023**	0.200232**	0.25686**	0.258974**
	(0.0088319)	(0.009989)	(0.022891)	(0.017515)
NSC	0.036229*	0.036229*	0.029058	0.055412**
	(0.018273)	(0.015243)	(0.039051)	(0.020843)
SLATE	0.040258**	0.040258**	-0.028060*	-0.034310**
	(0.0059368)	(0.005920)	(0.014768)	(0.011467)

[a] ** significant at 1% level. * significant at 10% level. Regression information for full sample OLS regression with White-corrected standard errors: R^2= 0.0862; Adjusted R^2 = 0.0857; Estimated variance (σ^2) = 0.13223; Sum of squared errors (SSE)= 4361.4; Mean of the dependent variable = 0.24534; Log of the likelihood function = -13433.4. Regression information for the full sample SUR regression: System weighted MSE 1 with 164154 degrees of freedom; System weighted R^2: 0.2718. Regression information for OLS regression with White-corrected standard errors: R^2= 0.1077; Adjusted R^2 = 0.1048; Estimated variance (σ^2) = 0.14354; Sum of squared errors (SSE)= 657.83; Mean of the dependent variable = 0.27636; Log of the likelihood function = -2053.97. Regression information for 1996 SUR regression: System weighted MSE: 1 with 45624; System weighted R^2: 0.3204

Table 5: Dependent Variable Greens: Selected estimated coefficients [a]

Variable (S.E.)	Full Sample Corrected OLS	SUR	1996 only Corrected OLS	SUR
Intercept	0.69536**	0.689459**	1.1061*	1.307888*
	(0.066134)	(0.073638)	(0.46392)	(0.637979)
NSC	0.034154	0.030680	1.0758**	1.022923**
	(0.031129)	(0.041182)	(0.13301)	(0.188208)
SLATE	-0.041821	-0.031831	0.98076**	0.927991**
	(0.033244)	(0.042671)	(0.13512)	(0.189332)

[a] ** significant at 1% level. * significant at 10% level. Regression information for full sample OLS regression with White-corrected standard errors:R^2= 0.2483; Adjusted R^2 = 0.2434; Estimated variance (σ^2) = 0.31768; Sum of squared errors (SSE)= 10415.; Mean of the dependent variable = 0.63065; Log of the likelihood function = -27797.1. Regression information for the full sample SUR regression: System weighted MSE 1 with 164154 degrees of freedom; System weighted R^2: 0.2718. Regression information for 1996 OLS regression with White-corrected standard errors: R^2= 0.2563; Adjusted R^2 = 0.2489; Estimated variance (σ^2) = 0.36944; Sum of squared errors (SSE)= 3364.1; Mean of the dependent variable = 0.71352; Log of the likelihood function = -8425.63. Regression information for 1996 SUR regression: System weighted MSE: 1 with 45624; System weighted R^2: 0.3204

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