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by

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Do Incentives Matter?
Product Quality and Contract Incentives in Processing Tomatoes

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Modern economics has developed a number of insights into the forces governing contratual 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 (in press) and Goodhue (1998).) 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 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 in press).

Tomato production contracts, commonly signed before planting, often include positive and negative monetary incentives to produce tomatoes with specified quality attributes. The processor may offer these quality incentives for moral hazard reasons or for production cost reasons. The contract incentives reduce the scope of any grower moral hazard regarding tomato quality, and mechanism design may be used to model the consequences of this reasoning. However, these payment specifications also allow the processor to minimize his cost of producing a final product with specific attributes by paying growers for the raw tomato attributes that result in the desired final product. In fact, the processor would minimize his production costs through the use of these quality incentives *even* if quality attributes were completely random (provided growers are not too risk averse). Hence, the two 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 following question: Do growers respond to contractually-specified marginal quality incentives? If growers do not respond to these incentives, it is unlikely that the quality incentives are designed to deal with a moral hazard problem. On the other hand, if growers do respond to these incentives

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

then 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 utilize a natural experiment regarding growers' responses to price incentives for processing tomato quality. In our data set, growers deliver processing tomatoes under a standard contract with price incentives, 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.

1. 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 *purely* a random variable 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.

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 $C_{Q,q} > 0$.[2] The derivatives over the choice variables are

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

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

The first order conditions determine the equilibrium levels of q and Q for the grower. 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

$$DET = \quad -(-w_q(B+p(q)) + p_q(1-w(q)) - C_{Q,q})^2 < \quad 0 \tag{4}$$

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

$$\frac{dq}{dB} = -\frac{(1-w(q))}{-w_q(B+p(q)) + p_q(1-w(q)) - C_{Q,q}} < \quad 0 \tag{5}$$

[2] 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.

$$\frac{dQ}{dB} = \frac{(w(q)-1)(Qw_{qq}(B+p(q))+2Qp_q w_q + C_{qq})}{DET} + \frac{-Qw_q}{-w_q(B+p(q))+p_q(1-w(q))-C_{Q,q}} > 0 \tag{6}$$

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 spot 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.

2. Data

Our data set contains quality information on all the tomatoes delivered to a given processor 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 spot 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 contratually-indicated, year-specific weeks *under the standard incentive contract* received a late season bonus worth between 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 predictions regarding yields.

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.

Data is 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, there are no weight adjustments for color, and loads are almost never rejected due to color.

3. 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. Conceptually, the model may be written as follows:

$$\begin{aligned}
\textbf{NTSS} &= f_1(\text{weather}, \underbrace{\text{grower's production practices}}_{+}, \text{tomato variety}, \underbrace{\text{time of season}}_{+}) && (7)\\
\textbf{LU} &= f_2(\text{weather}, \underbrace{\text{grower's harvest decision}}_{-}, \text{tomato variety}) && (8)\\
\textbf{Mold} &= f_3(\text{weather} : \underbrace{\text{rain}}_{+}, \underbrace{\text{grower's sorting practices}}_{-}) && (9)\\
\textbf{Greens} &= f_4(\text{weather}, \underbrace{\text{grower's sorting practices}}_{-}, \text{tomato variety}) && (10)\\
\textbf{MOT} &= f_5(\underbrace{\text{grower's sorting practices}}_{-}) && (11)
\end{aligned}$$

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 absence of incentives.

If the grower wants to increase NTSS for a given variety, the grower can choose an irrigation and fertilizing regime to increase NTSS. However, increasing NTSS comes at the expense of yield, making NTSS the most expensive quality to deliver.[3] If the standard contract incentives are sufficiently

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

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:

$$\mathbf{NTSS} = \beta_1 + \underbrace{\beta_{\text{NSC}}}_{-}\text{NSC} + \underbrace{\beta_{\text{SLATE}}}_{\text{indet.}}\text{SLATE} + \beta_V V_i + \beta_{WY} WY_j + \beta_g g_k + \beta_{gV} gV_{k,i} + \epsilon_{\mathbf{NTSS}} \quad (12)$$

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 harvesttime 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. The grower can influence the share of limited use tomatoes through his harvesting decisions. A highly skilled grower will choose the time of the harvest to maximize the share of ripe tomatoes and minimize the share of LU tomatoes. For instance, since hotter weather increases the likelihood of LU tomatoes, the grower may choose to harvest at night when it is cooler. If the grower mistimes the harvest, the grower can increase sorting effort to deliver a load with a small share of LU tomatoes. The mechanical sorter is not very effective at removing LU tomatoes, and labor is relatively expensive, so sorting is a relatively costly way of reducing the share of LU tomatoes in the total delivered. 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 nonstandard 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 estimable equation for (9) is

$$\mathbf{LU} = \beta_2 + \underbrace{\beta_{\text{NSC}}}_{+}\text{NSC} + \underbrace{\beta_{\text{SLATE}}}_{+}\text{SLATE} + \underbrace{\beta_{\text{NIGHT}}}_{-}\text{NIGHT} + \beta_V V_i + \beta_{WY} WY_j + \beta_g g_k + \beta_{gV} gV_{k,i} + \epsilon_{\mathbf{LU}} \tag{13}$$

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 is generally a potential problem only for tomatoes harvested in the latter part of September. If there are heavy rains, the grower may lose his entire tomato crop. 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 high percentage of green tomatoes and a lower sugar content, which reduces payments for other quality attributes.[4] 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:

[4] Our preliminary analysis can not account for these interaction effects. We are currently working on alternative estimation techniques that will include these effects.

$$\textbf{Mold} = \beta_3 + \underbrace{\beta_{\text{NSC}}}_{+}\text{NSC} + \underbrace{\beta_{\text{SLATE}}}_{+}\text{SLATE} + \beta_{WY}WY_j + \beta_g g_k + \beta_{gV} gV_{k,i} + \epsilon_{\textbf{ Mold}} \tag{14}$$

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. In order to deliver a load with few greens and MOT, the grower merely has to increase the sensitivity of the mechanical sorter on the tomato harvester. 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 $\epsilon_{\textbf{ MOT}}$ is the error term, specifies (11) appropriately:

$$\textbf{MOT} = \beta_5 + \underbrace{\beta_{\text{NSC}}}_{+}\text{NSC} + \underbrace{\beta_{\text{SLATE}}}_{+}\text{SLATE} + \beta_g g_k + \epsilon_{\textbf{ MOT}} \tag{15}$$

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:

$$\textbf{Greens} = \beta_4 + \underbrace{\beta_{\text{NSC}}}_{+}\text{NSC} + \underbrace{\beta_{\text{SLATE}}}_{+}\text{SLATE} + \beta_V V_i + \beta_{WY}WY_j + \beta_g g_k + \beta_{gV} gV_{k,i} + \epsilon_{\textbf{ Greens}} \tag{16}$$

4. Results

Applying ordinary least squares by equation results in a failed White's test for heteroskedasticity. Thus we report least squares regressions by equation with White's corrected standard errors. Currently, we are developing econometric models that will correct for the heteroskedasticity (and account for the interactions discussed earlier) to verify our results. Overall, the preliminary results reported here support the hypothesis that growers do respond to quality incentives. With the exception of NTSS, which had the opposite sign, and greens, which was insignificant, the non-standard contract tomatoes are of lower quality than standard contract tomatoes. The results support the hypothesis that growers respond to the contract incentives when the contract incentives are sufficiently large to cover the costs of providing high quality tomatoes.

NTSS: For the equation with NTSS as the dependent variable, the coefficient on NSC was positive and significant. This not only contradicts our null hypothesis but it is counterintuitive because it implies that growers deliver higher quality without incentives. This result is likely due to the dominance of biological factors over 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.

LU: The coefficient on the non-standard contract dummy was positive and significant; 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 but insignificant. 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 mold, we reject the null that growers do not respond to the contract incentives. In addition 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.

Greens: For the equation with Greens as the dependent variable, the coefficients on NSC and Slate were both 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.

5. Conclusion

We utilize data on tomatoes delivered under a price incentive contract and a fixed price to examine if growers respond to price incentives. Overall, our results are consistent with the hypothesis that growers respond to price incentives by increasing tomato quality. Both the nonstandard contract variable and the standard contract late season coefficients had the predicted sign in the regressions for limited use tomatoes, mold, and material other than tomatoes. All were significant except for the limited use tomato nonstandard contract coefficient. In the equation for net soluble solids (NTSS), both coefficients had the opposite sign and were significant, indicating that for this particular attribute biological considerations dominated incentive considerations. In the equation for green tomatoes, both coefficients were insignificant, which may be due at least in part to the relatively small price incentives offered for this attribute. Of course, our reported results must be regarded as preliminary, since we do not account for interactions across attributes.

This analysis undertook 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 contract theory is an appropriate way to model these contracts. Evidence of grower response is not sufficient to identify an asymmetric information problem.

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

Variable	Est. coeff.	s.e.	t-ratio	p-value
Intercept	4.9397	0.040759	121.19	0.0000
NSC	0.15710	0.027028	5.8126	0.0000
SLATE	0.086883	0.030360	2.8618	0.0042

[a] 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; t-ratio 32786 DF

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

Variable	Est. coeff.	s.e.	t-ratio	p-value
Intercept	1.3817	0.14224	9.7140	0.0000
NSC	0.27189	0.085705	3.1724	0.0015
SLATE	0.070419	0.088603	0.79476	0.4268
NIT	-0.33725	0.016758	-20.125	0.0000

[a] 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; t-ratio 32785 DF

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

Variable	Est. coeff.	s.e.	t-ratio	p-value
Intercept	-0.47723	0.12541	-3.8054	0.0001
NSC	0.29537	0.079498	3.7154	0.0002
SLATE	0.55895	0.074660	7.4866	0.0000

[a] 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; t-ratio 32815 DF

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

Variable	Est. coeff.	s.e.	t-ratio	p-value
Intercept	0.20023	0.0088319	22.672	0.0000
NSC	0.036229	0.018273	1.9827	0.0474
SLATE	0.040258	0.0059368	6.7811	0.0000

[a] 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; t-ratio 32982 DF

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

Variable	Est. coeff.	s.e.	t-ratio	p-value
Intercept	0.69536	0.066134	10.514	0.0000
NSC	0.034154	0.031129	1.0972	0.2726
SLATE	-0.041821	0.033244	-1.2580	0.2084

[a] 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; t-ratio 32786 DF

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