

ON THE EFFICACY OF CONTRACTUAL PROVISIONS FOR PROCESSING TOMATOES

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ABSTRACT. This paper uses extensive data on production outcomes for processing tomato growers in California to examine the efficacy of explicit incentives observed in grower-processor contracts. Our data include all deliveries of tomatoes to some 51 processors over a period of 7 years in which at least 65 unique types of contracts are employed. Results indicate that incentives account for a significant proportion of observed variation in production outcomes, and that complementarities across different sorts of “incentive instruments” play a prominent role in contract design. Also, explicit incentives observed in actual contracts explain a substantial portion of the variation in production outcomes, but there remains considerable variation which might be accounted for by implicit incentives offered by the processors. Finally, though we control for a large set of factors that might conceivably affect expected production outcomes, we are left with a substantial amount of unexplained variation.

1. INTRODUCTION

The production of processing tomatoes in California is generally governed by a contract written between one of a number of processors and individual growers. One important problem addressed by these contracts has to do with the provision of incentives for the growers to produce tomatoes of high quality.

We have obtained data on the measured quality of most of the ‘loads’ of processing tomatoes produced in California over a seven year period, and can observe the contractual provisions relating grower compensation to measured quality for each of these loads. In this paper, we attempt to measure the efficacy of these contractual provisions by estimating the effect of various of these provisions (both alone and in

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combination) on the conditional means of measured quality characteristics.

Other authors have attempted to address this question [Alexander et al. (1999); Wu (2001); Meng (2002)], but have generally found that incentives provided in these contracts are of minor importance, or have no significant effect on outcomes. We would argue that none of these earlier efforts adequately controlled for the considerable heterogeneity due to differences across growers, varieties of tomato, or location. After taking account of these possible sources of heterogeneity, we estimate an upper bound on the variance in quality outcomes which *could* be due to the provision of incentives; we then see how much variance is actually accounted for by variation in the sorts of premia explicitly offered in the tomato contracts.

Finally, people in the processing tomato industry draw a distinction between quality characteristics for which growers are rewarded *premia* in contracts versus those for which growers are punished by use of *deducts*. Most observed contracts make grower compensation per ton a piecewise-quadratic function of quality characteristics; what those in the industry call premia correspond to characteristics for which the grower's compensation has a linear component. While this paper does *not* address the efficiency of contracts, the form taken by compensation is very suggestive. Possible avenues for modeling the problem of contract design might involve pursuing a model of multitasking (Holmström and Milgrom (1991); Laffont and Martimort (2002)), in which compensation may take a linear form (where only "local incentive compatibility" constraints are binding), or a (possibly simpler) model in which linearity in some quality measures follows from the independence of quality measures conditional on agents' actions, logarithmic utility, and the validity of the "first order approach" (Hueth and Ligon (1999a,b)).

2. OBSERVED CONTRACTS

California is the largest producer of processing tomatoes in the United States, typically accounting for over 95 per cent of total annual production (over 10 million tons in 1998). Tomatoes growers vary widely in the size of their operations. Figure 1 displays a Lorenz curve for growers and their respective contributions to total industry production over the period 1993–99. There were 519 total growers in these years, and fewer than 10 per cent of these accounted for 41 per cent of total production.

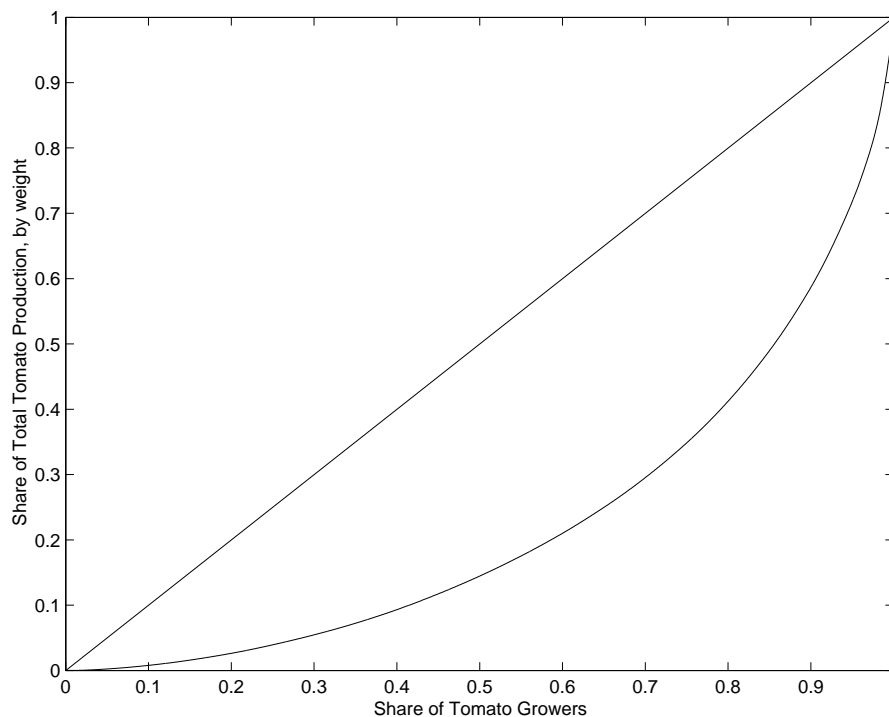


FIGURE 1. Lorenz Curve Illustrating Inequality in Tomato Production (by weight).

There were 51 processors in California who bought tomatoes in one or more of the years 1993–99. Among these processors there’s considerable variation in how tomatoes are obtained. Two processors are cooperative ventures owned by tomato growers, which obtain most of their tomatoes from member growers. Some small proportion of tomatoes obtained by processors is purchased on spot markets.¹ However, the vast bulk of processing tomatoes are grown by farmers under a contract negotiated before planting.

Two important institutions mediate exchange between growers and processors in California. The California Tomato Growers Association (CTGA) is a bargaining entity that negotiates contract terms with processors on behalf of member growers. Membership in this organization fluctuates from year to year, but generally accounts for between 65%

¹Alexander et al. (1999) uses this fact to examine quality differences between tomatoes obtained under a contract and on spot markets, but only by a single processor in a single year using a single contract; accordingly, they are unable to draw any inference regarding the effect of any of the provisions of the contract.

and 70% of growers. The Processing Tomato Advisory Board (PTAB) performs third-party quality measurement and is jointly funded by processors and growers. All loads delivered by growers must be inspected at a certified PTAB grading station; the standard quality attributes measured for each load include weight, sub-skin color (“comminution”), the proportion of unripe tomatoes (“green”) and a measure of sugar content (“soluble solids”); also measured are various sorts of damage: tomatoes with soft spots (“limited use”), mold, worms, and finally “material other than tomatoes” (dirt clods, tomato vine, etc.) which may make up part of the load.

The CTGA and PTAB each play a key role in determining the contractual arrangements which govern the relationship between growers and processors. In particular, since PTAB supplies information on quality measurement to both parties, these quality measures can be used to help determine the payments made to farmers under contract. The CTGA plays a complementary role, by annually negotiating a “master” contract with many of the processors (161 of 262 total contracts over the period 1993–99) which specifies the way in which quality measures affect grower compensation, the conditions under which processors may “reject” loads of tomatoes, and which provides explicit mechanisms for resolving disputes between growers and processors.

There are many points of commonality among the contracts negotiated by the CTGA. Although the CTGA is involved in negotiating over the ways in which quality measurements affect grower compensation, individual processors negotiate with individual farmers over *how many* tomatoes the grower is to provide. In years past, many processors committed to purchase all of the tomatoes grown on some fixed number of acres. This arrangement still appears as an option in some years for one of the processors whose contracts we observe, but otherwise processors now commit to accept a fixed number of ‘loads’ of tomatoes, though if the grower should happen to produce somewhat more than this quantity the processor may choose to accept these additional loads (otherwise the extra loads will probably be sold on the spot markets alluded to above). Though contracts are negotiated annually, there may be implicit dynamic incentives, as farmers who have performed well in past years are rewarded with increases in the number of loads the processor commits to accept. For all CTGA negotiated contracts, the growers’ compensation is based on the number of tons delivered, and is adjusted according to the outcome of the various quality attributes measured by the PTAB.

For many of the contracts negotiated by the CTGA, the way in which quality measurements influence compensation for a given load

has a ‘standard’ piecewise-quadratic form. Even this standard form permits a great deal of variation—a quadratic form in the seven measured quality characteristics (plus linear terms) requires one to specify 36 coefficients (though many of these are observed to always be zero), but each of these coefficients may vary in a piecewise fashion depending on the measured level of the corresponding quality attributes, so that observed contracts are not only non-linear, but are in fact also highly ‘non-quadratic.’ Moreover, a considerable proportion of CTGA-negotiated contracts augment this standard form by adding conditions which induce various forms of dependence either across loads delivered by a given grower, or across growers (this latter can be regarded as a form of relative performance evaluation).

One important line of research pursued by Wu (2001) seeks to explain the reasons for the variation observed in contracts—since they appear to be solving similar problems with their contracts, why is it that processors don’t all adopt the same contract? Wu’s answer is that since different processors use tomatoes for different purposes, they value different tomato attributes differently. For example, processors who make tomato paste may find it worthwhile to offer a larger premium for “soluble solids,” than ketchup producers. Another possibility might relate differences in the contractual terms offered by various processors to differences in their environments; since it’s costly and difficult to transport ripe tomatoes over great distances, most processors obtain the tomatoes they use from nearby growers, and a well-designed contract ought to take advantage of differences in climate, soil, or the distribution of characteristics of nearby growers.

3. MODEL

We begin with a brief description of the environment. There are L processors, indexed by $\ell = 1, \dots, L$. Collectively, these processors process y “loads” of tomatoes, indexed by $j = 1, \dots, y$. A given load j is grown by one of n growers indexed by i ; we choose to regard the identity of this grower as a characteristic of load j , and denote this grower by i_j . A load of tomatoes j also has other characteristics, including the location (district) in which it was grown (d_j), the time (month and year) at which it was harvested (m_j, t_j), and (critically for our purposes), a vector of measured quality characteristics q_j , with conditional distribution $G(q_j | a_{i_j}, b_{i_j}, d_j, m_j, t_j)$.

The identity of the grower of load j is of particular interest, because the grower also possesses some important characteristics. Some of these are assumed to be invariant over time (e.g., industriousness,

soil characteristics of farm operated by i , preferences); we denote these invariant grower characteristics by the vector b_i . Other characteristics may be time varying, or depend on choices made by the grower (e.g., management decisions such as how much fertilizer to use); these we denote by the vector $a_{i,t}$.

As with growers, though some characteristics of tomato loads are fixed (e.g., district), others are not. In particular, we take the quality characteristics of load j to be a function of other characteristics according to u_j .

$$(1) \quad q_j = \phi(a_{i_j,t_j}, b_{i_j}) + \lambda(d_j, m_j, t_j) + u_j,$$

where the vector-valued function ϕ captures the influence of grower characteristics on quality outcomes, the vector-valued function λ captures the influence of location and date of harvest, and the disturbance term u_j summarizes the influence of unobservables. This disturbance term u_j has a distribution $F(u)$, and is assumed to be orthogonal to $\phi(a_{i_j,t_j}, b_{i_j})$, $\lambda(d_j, m_j, t_j)$, and to any characteristics of the processor to which load j is delivered.

So far, our description of the environment has been essentially a description of technology, of the mapping from inputs and characteristics into outcomes (quality measures). However, among the most important of the inputs to tomato quality production are the actions and decisions taken by the grower, who in turn chooses these based on the incentives and constraints he faces. In particular, we assume that the grower values the revenue he derives from selling his tomatoes. This revenue, in turn, will generally depend on the terms of the contracts offered growers by processors; variation in these contracts can be summarized by a vector of contractual provisions π which, among other things, conditions payments for load j on realized quality characteristics q_j , and possibly on a vector of other variables x . Accordingly, we write the compensation received for a load of tomatoes having characteristics (q, x) under a contract with provisions π as $w(q, x; \pi)$. Set against these revenues are the cost incurred by a grower having characteristics b who takes actions a which we write $c(a, b)$.

The grower is assumed to have von Neumann-Morgenstern preferences, with utility function $U : \mathbb{R} \rightarrow \mathbb{R}$. Accordingly, a grower i who delivers loads of tomatoes to a processor ℓ in year t chooses his actions by solving

$$(2) \quad a_{i,t} \in \operatorname{argmax}_a \int U \left(\sum_{\{j|i_j=i\}} w(q_j, x_j; \pi_\ell) - c(a, b_i) \right) dG(q_j|a, b_{i_j}, d_j, m_j, t_j).$$

Thus, (2) yields a decision rule which maps contractual provisions, fixed grower characteristics and other variables x into a set of management decisions $a_{i,t}$ taken by the grower. These management decisions in turn influence the distribution of quality outcomes.

4. DATA

We have obtained data on characteristics of over 1.6 million loads of processing tomatoes harvested over the period 1993-99, accounting for roughly 65 per cent of all the processing tomatoes produced in California during this period. Each of these loads of tomatoes was “graded” at one of 45 grading stations in the state, and then delivered to one of 51 processors.

	Solids	Worms	Comm.	Green	Mold	MOT	LU
Grower-Year	0.2455	0.0429	0.3063	0.2438	0.2072	0.1194	0.2128
District-Month-Year	0.0229	0.0186	0.0405	0.0264	0.0831	0.0038	0.0286
Variety-Year	0.1988	0.0136	0.2204	0.0789	0.1313	0.0230	0.1536
Processor-Year	0.0599	0.0237	0.1520	0.1079	0.0625	0.0212	0.0665
R^2	0.3673	0.0686	0.4072	0.2907	0.3238	0.1316	0.3220

TABLE 1. ANOVA Results for Quality Measures

Processing tomatoes are harvested over a roughly five month period, beginning in June and ending in September, starting in the southern part of the state and moving north over the course of the summer. However, although the volume of tomatoes strongly depends on time and location, surprisingly little of the variation observed in quality characteristics is due to location and the time of harvest. The second row of Table 1 reports (for each of seven quality measures) the proportion of variance in quality accounted for by conditioning on the district, month, and year of harvest. There are 10 districts, five months, and seven years of data, so we are in effect reporting the R^2 statistic from a simple OLS regression of each of these quality characteristics on a set of 350 dummy variables. Time and location explains eight per cent of the variation in measured mold, four per cent of the variation in color (measured by “comminution”), and somewhat less than three per cent of the variation in limited use (rotten) tomatoes. ‘Material other than tomatoes’ seems to have very little dependence on location and time; roughly two per cent of the variation in the remaining measures is accounted for by these time and location dummies.

Much more variance in quality characteristics is accounted for by information on grower-year, the latent variable we estimate to measure the effects of grower type and effort. Though we have data on 533 growers over seven years, not all of these growers produced tomatoes in every year, so that we have a total of 2026 distinct grower-years. These grower characteristics account for as much as 30 per cent of the variation observed in color, and about 24 per cent of the variation in solids and green. Roughly 21 per cent of the variation in Mold and LU are accounted for by these latent variables, while twelve per cent of MOT and 4 per cent of worms seems to be explained by this grower-year variation.

Finally, a considerable but somewhat smaller amount of variation is accounted for by the variety of tomato comprising a load, along with the year in which those tomatoes are grown. There are 394 different tomato varieties which appear in our data over seven years, yielding 1198 variety-year dummies which collectively account for twenty-two per cent of variation in comminution, twenty per cent of solids, fifteen per cent of limited use, and thirteen per cent of mold; variation in worms, green and mold varies much less with variety-year, with the latter accounting for one, eight, and two per cent of variation respectively.

5. EMPIRICS

Our aim in this paper is to estimate the effects that various possible contractual provisions have on the quality characteristics of processing tomatoes. We have extensive data on these quality characteristics; we surmise that the distribution of these characteristics depends on both aspects of the environment (weather, soil, tomato variety), but also on decisions and actions taken by the grower.

If we had data on the actions taken by growers, we might find it tempting to regard (1) as an estimating equation. However, simply estimating the functions ϕ and λ in this equation in isolation would not be a good strategy, as the whole point of our present exercise has to do with the endogeneity of actions; obtaining consistent estimates would require either the simultaneous estimation of (1) and (2), or the use of instrumental variable techniques.

As in fact we do not observe data related to the actions taken by growers, we are preserved from temptation. We reformulate the system of equations (1) using district-month dummies (we have seven years of data; there are 10 districts, and five months in which processing tomatoes are harvested, for a total of 350 dummy variables) to estimate

the latent variable $\lambda(d_j, m_j, t_j)$, so that we have

$$(3) \quad q_j = \phi(a_{i_j, t_j}, b_{i_j}) + \alpha_{d_j, m_j, t_j} + u_j.$$

The term $\phi(a_{i_j, t_j}, b_{i_j})$ is problematic, of course: we don't know the function ϕ , and we don't observe its arguments. However, knowledge of contractual provisions and other variables allows us to construct a decision rule for actions a . Let us denote the vector of observed variables which determine actions by z , and define a disturbance term $v_{i,t}$ by

$$(4) \quad \phi(a_{i,t}, b_i) = z'_{i,t} \Gamma + v_{i,t}.$$

We assume that Γ is such that $E(v_{i,t} | z_{i,t}) = 0$ for all growers i and all years t ; we further assume that $E(u_j | z_{i_j, t_j}) = 0$ for all j .

We use (4) to replace the term in (3) involving ϕ , yielding the system of estimating equations

$$(5) \quad q_j = z'_{i,t} \Gamma + \alpha_{d_j, m_j, t_j} + u_j + v_{i_j, t_j};$$

given our assumptions regarding the orthogonality of $z_{i,t}$ and the disturbance terms, OLS yields consistent estimates of parameters of this estimating equation, and in particular of the parameters of interest Γ .

We propose to compare two different possible sets of coefficient estimates Γ . Since each processor offers only a single contract in any given year, we will first choose for z_{i_j, t_j} a collection of processor-year dummy variables; given the linear specification of our estimating equation, the proportion of variation in quality measures accounted for by this collection of dummy variables represents an upper bound on the amount of variation which can be explained by a collection of processor/contract characteristics. Of course, while some of the variation explained by this collection of dummy variables may be due to variation in contractual incentives, some may also be due to processor characteristics (e.g., scale, location, quality of field staff) not directly related to the provision of incentives. Accordingly, we also work with a second set of possible z_{i_j, t_j} variables, corresponding to different attributes of the contracts offered to growers. While the estimated coefficients in the Γ matrix corresponding to these contractual provisions are of central importance in this paper, the proportion of variance accounted for by these characteristics *relative* to the proportion accounted for by the processor-year dummies gives us a metric for understanding how well the contract variables we've introduced perform in accounting for the total variation in quality due to differences across processors and years.

6. RESULTS

Table 2 summarizes the effect of variation in processors' contract incentive schedules on quality outcomes. In this table, total annual volume for each processor (measured in millions of tons) is significant in the equations for solids, Comm., and LU. Holding all else equal, large volume processors receive tomatoes that are on average higher in soluble solids, but also higher in comminution, and with a greater limited use proportion.

Given the particular structure of processing tomato contracts described earlier, an increase in the base price increases marginal incentives for reducing damage, but has no effect on marginal incentives for quality attributes which receive premia (or, if increases in quantity can be obtained by the expense of these quality measures, increases in base price may well have a negative effect). The negative and significant base-price coefficients in the solids and LU equations are both consistent with this observation. When base price rises, the payoff from reducing LU rises relative to the payoff from increasing solids, and growers apparently respond accordingly. However, the negative and significant coefficient on comminution seems to run counter to this intuition.

To summarize the effect of contract incentives on quality outcomes, we first created premium and deduct indicators for each quality measure. All processors offer some form of deduct on MOT, LU, worms, green, and mold, and no processor deducts for low soluble solids or high Comm.. In contrast, there is substantial variation in the set of measures that are awarded premiums. Because we expect significant interaction between the various kinds of quality incentives, we created a further set of indicators for each unique *set* of quality premium awarded. The base contract that is omitted from our regression offers no type of quality premium. The next contract type, labeled "Solids" in Table 2, offers only soluble solids incentives, the contract type labeled "Solids, MOT" offers incentives on soluble solids and MOT, and so on. Thus, the coefficients for each indicator measure the effect of the respective contract type, relative to the base contract with no quality premiums.²

The first thing to note about the coefficients on these indicators is that they are highly significant: incentives do matter. Even after controlling for a quite comprehensive set of factors that might conceivably

²Although there is variation across processors in the *specific* deduct premium schedules employed (e.g., one processor might offer a bonus of \$1 for soluble solids above some given amount, while another processor might offer \$1.50), we choose to ignore this variation for the present.

	Solids	Worms	Com.	Green	Mold	MOT	LU
Volume	0.0000*	-0.0000	0.0002*	0.0001*	0.0001*	0.0000	0.0001*
	(11.9905)	(-1.6078)	(21.5977)	(16.4413)	(9.1804)	(1.5869)	(16.6088)
Base Price	-0.0003*	-0.0000	-0.0012*	-0.0003*	-0.0005*	0.0000	-0.0006*
	(-14.5921)	(-1.0690)	(-13.0360)	(-10.4908)	(-8.0683)	(1.9095)	(-7.0710)
Solids	-0.0006	0.0012*	-0.0795*	-0.0138*	0.0405*	-0.0077*	-0.0199*
	(-0.5726)	(4.6460)	(-13.9586)	(-6.6198)	(11.3447)	(-6.9009)	(-3.9884)
MOT	-0.0180*	0.0010*	0.0125	-0.0160*	-0.0037	-0.0011	-0.0722*
	(-12.5563)	(2.9546)	(1.7123)	(-5.9904)	(-0.8067)	(-0.7441)	(-11.2679)
MOT, Solids	0.0444*	0.0013*	0.0059	-0.0181*	-0.0273*	-0.0152*	-0.0878*
	(26.4121)	(3.2099)	(0.6953)	(-5.7878)	(-5.0844)	(-9.0243)	(-11.6981)
LU	0.0386*	-0.0037*	-0.0004	-0.0375*	-0.0810*	-0.0082*	-0.0160
	(14.0334)	(-5.7510)	(-0.0270)	(-7.3231)	(-9.2241)	(-2.9709)	(-1.3031)
LU, Solids	0.0580*	0.0018*	-0.1835*	-0.0194*	0.0319*	-0.0164*	-0.0554*
	(22.3470)	(2.8928)	(-13.8891)	(-4.0218)	(3.8561)	(-6.3235)	(-4.7772)
LU, MOT	0.0028*	0.0012*	-0.0997*	-0.0012	0.0499*	0.0013	-0.0147*
	(2.5805)	(4.8819)	(-18.2781)	(-0.5900)	(14.5798)	(1.2519)	(-3.0709)
LU, MOT, Solids	0.0496*	0.0018*	0.0286*	-0.0252*	-0.0335*	-0.0075*	-0.0387*
	(20.7510)	(3.1519)	(2.3580)	(-5.6851)	(-4.3954)	(-3.1259)	(-3.6265)
LU, Mold, MOT, Solids	0.0259*	0.0032*	0.0506*	0.0058	-0.0466*	-0.0072*	-0.0681*
	(9.3122)	(4.8295)	(3.5728)	(1.1194)	(-5.2451)	(-2.5765)	(-5.4807)
Comm, Solids	0.0114*	0.0032*	-0.0486*	0.0174*	0.0700*	0.0077*	-0.1587*
	(4.1904)	(4.9646)	(-3.4958)	(3.4363)	(8.0373)	(2.8201)	(-13.0177)
Comm, LU	-0.0009	0.0004	0.1237*	-0.0165*	-0.0535*	-0.0093*	-0.0559*
	(-0.6042)	(1.1234)	(16.8516)	(-6.1335)	(-11.6191)	(-6.4616)	(-8.6737)
Comm, LU, Solids	0.0050*	-0.0002	-0.0793*	-0.0056*	-0.0382*	-0.0049*	-0.0730*
	(3.9522)	(-0.5067)	(-12.2959)	(-2.3554)	(-9.4571)	(-3.8425)	(-12.8969)
Comm, LU, MOT	-0.0306*	0.0002	-0.0538*	-0.0116*	-0.0326*	0.0028	-0.0713*
	(-16.4195)	(0.3429)	(-5.6659)	(-3.3489)	(-5.4826)	(1.5052)	(-8.5608)
Comm, LU, MOT, Solids	-0.0070*	-0.0015*	-0.1731*	-0.0132*	-0.0563*	0.0006	0.0369*
	(-2.7416)	(-2.4881)	(-13.2531)	(-2.7550)	(-6.8692)	(0.2327)	(3.2155)
Comm, Green, LU, MOT	-0.0377*	0.0069*	0.0483	0.1434*	0.1142*	0.0176	0.0401
	(-3.1173)	(2.4198)	(0.7852)	(6.3802)	(2.9635)	(1.4566)	(0.7428)
R^2	0.3634	0.0660	0.4024	0.2857	0.3203	0.1307	0.3186
Relative Efficiency	0.2261	0.0381	0.1560	0.0426	0.1029	0.1165	0.0899

TABLE 2. Regression Results for Quality Measures. Each column corresponds to a particular regression; figures in parentheses are t -statistics. Each regression also includes the collection of dummy variables described in the first three rows of Table 1 and a constant, and are estimated subject to the restriction that each set of dummy variables must sum to zero. The penultimate row gives R^2 statistics for each regression equation, while the final row gives the ratio of the marginal increase in R^2 due to the variables reported in the table divided by the marginal increase in R^2 which results from instead adding a set of processor-year dummies.

affect realized quality outcomes (other than contract incentives), the contract type indicators still add substantial explanatory power.

Perhaps the most striking aspect of the results in Table 2 is the degree to which complementarities across the various incentives terms are important. For example, a contract that offers only solids premium does nothing significant in terms of expected solids outcomes. However, combining MOT or LU incentives with the solids incentives, or combining all three types of incentives, results in strong positive effects on expected solids outcomes. Also, note that many of the contract types that *exclude* any form of solids incentives, with the notable exception of the LU contract, lead to relatively low expected solids.

Incentives for comminution are never offered in isolation, and result in higher expected quality (lower comminution) when they're combined with incentives for either solids, LU and solids, LU and MOT, or when combined with incentives for LU, MOT, and solids. Perhaps surprisingly, expected quality falls when comminution and LU incentives are bundled. Even though the sign of this effect seems somewhat counterintuitive, it is still consistent with the notion that the incentives offered by processors have their intended effect. For example, imagine that some processor places a particularly high value on low levels of LU, relative to other measures of quality. How might we expect this processor to design its incentive schedule? Looking at Table 2, it's apparent that offering just LU incentives won't achieve much. The processor can achieve low expected LU by offering incentives for a variety of quality measures *other* than LU (e.g., MOT, solids and MOT, Comm. and solids), but these incentives induce high expected levels for measures about which the processor cares very little. Alternatively, the processor can choose between offering incentives for LU and Comm., LU, solids, and Comm., or LU, MOT, and Comm.. Each of these combinations has the intended effect of reducing expected LU, and depending on the processor's valuation of solids, MOT, and Comm. outcomes, any of these combinations may be adequate. If in addition to LU, the processor values low levels of MOT, but cares little about solids and Comm., the contract type that combines LU and Comm. incentives will be preferred, and this results in relatively high levels of expected Comm. (though the intended effect is to reduce expected LU).

Each of the significant coefficients in the MOT equation for contract types that contain some form of MOT premium are negative. The same is true in the LU equation (for coefficients with some form of LU premium), with the exception of the contract type that offers incentives for Comm., LU, MOT, and solids. Interestingly, this particular contract also happens to have a large effect on expected Comm. outcomes so

that a similar interpretation to the one provided above for the LU and Comm. contract can be provided for this seemingly counterintuitive result.

In Table 2, the base price coefficient has the expected sign in each equation, and is significant in the equations for green and mold. A high base price provides relatively strong incentives for reducing damage, and growers are able to respond effectively for the green and mold measures.

From the quality characteristics discussed above, we turn to a set of quality characteristics reported in Table 2 which are primarily measures of ‘damage,’ and which almost without exception do not receive quality premiums.³ Since each of these contracts was offered only once, it’s conceivable that they represent processor ‘experiments’ with negative outcomes. The strong positive effect of the green premium seems consistent with this hypothesis. The mold premium *did* lead to lower average levels of mold, but also to higher average levels of worms. There is very little variation in worms to be explained, and as a result, coefficients in the worms equation are generally less significant than in any of the other equations. Nearly all of the contract types, with the notable exception of the one contract that offers green incentives discussed above, and another contract with Comm. and solids incentives, seem to provide effective incentives for reducing expected green outcomes. In contrast, there are five types of contracts that generally lead to poor outcomes in terms of mold. These include the contracts for solids, LU and solids, LU and MOT, Comm. and solids, and Comm., green, LU, and MOT.

7. CONCLUSION

We use data from California’s processing tomato industry to investigate the influence of contract incentives on realized production outcomes. Our data are generated from the activities of roughly 51 processors who collectively contracted with approximately 250 tomato growers in each year during the period 1993-99. Though contracts for processing tomatoes in California all have a similar generic structure, details vary considerably across processors and years. In this paper, we examine the extent to which this variation can explain differences in production outcomes across processors.

³The exceptions include a single processor who in 1997 awarded premium for low mold, and a another processor who in 1998 awarded premium for low green.

Even after controlling for an exhaustive set of factors that might conceivably effect expected production outcomes (grower-year, location-month-year, and variety-year effects), contract incentives do indeed matter. Because each processor offers a single contract in a given year, processor-year effects provide an upper bound for the amount of variation in production outcomes that might be explained by differences in contract terms across processors. Relative to this upper bound, the much more parsimonious set of variables we include to reflect premia offered in these contracts perform surprisingly well. This suggests that much of the variation in contract incentives across processors *is* captured in the explicit contracts we observe, though one can imagine many sorts of indirect or implicit incentives that might also be important.

The specific effects observed for different contract types are generally consistent with what one would expect: when the premium awarded on a particular quality measure goes up, this leads to higher expected outcomes in the same measure. Also, with only one exception, variation in base price has the anticipated consequence that growers shift their attention to quality measures that show up as “deducts” in processors’ incentive schedules. This in turn leads to lower levels for measures that only receive “premia”.

A somewhat surprising aspect of our results is the degree to which complementarities across different types of incentive instruments are important. Almost without exception, the combined effect of multiple incentive premiums generally has a larger and more significant effect on expected quality outcomes than any single premium. Alternatively, offering incentives on just one or a few types of quality measures can have a variety of (possibly) unintended consequences. The fact that some contracts were offered during a short period and then subsequently discontinued suggests that processors experiment with alternative contract designs, and that contract design is a delicate task.

For the purpose of this paper, we have intentionally been agnostic regarding the *efficiency* of the contracts we observe. Our only aim has been to characterize the empirical relevance of variation in contract provisions across processors and years. A natural next step in this line of research is to examine how well the contracts we observe match up with theory. For example, the additive separability of various quality measures observed in tomato processing contracts imply something quite specific about the structure of the production technology governing production outcomes. In particular, additive separability of the compensation growers receive in the form of quality premia requires some form of conditional independence across measures, and one could

conceivably test for such independence. A more ambitious exercise would be to compare estimates of an efficient contract with those actually observed (see Haubrich and Popova (1998) and Hueth and Ligon (2002) for progress in this direction).

REFERENCES

- Alexander, C., R. E. Goodhue, and G. C. Rausser (1999). Product quality and contract incentives in processing tomatoes. Manuscript.
- Haubrich, J. G. and I. Popova (1998). Executive compensation: A calibration approach. *Economic Theory* 12, 568–581.
- Holmström, B. and P. Milgrom (1991). Multitask principal-agent analyses: Incentive contracts, asset ownership, and job design. *Journal of Law, Economics, and Organization* 7(0), 24–52.
- Hueth, B. and E. Ligon (1999a). Agricultural supply response under contract. *American Journal of Agricultural Economics* 81(3), 610–615.
- Hueth, B. and E. Ligon (1999b). Producer price risk and quality measurement. *American Journal of Agricultural Economics* 81(3), 512–524.
- Hueth, B. and E. Ligon (2002). Estimation of an efficient tomato contract. *European Review of Agricultural Economics Forthcoming*.
- Laffont, J.-J. and D. Martimort (2002). *The Theory of Incentives : The Principal-Agent Model*. Princeton University Press.
- Meng, X. (2002). The effects of contracts on quality of California processing tomatoes. Unpublished manuscript.
- Wu, S. (2001). *Product Choice, Incentives, and Risk-Sharing*. Ph. D. thesis, University of California, Berkeley.

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