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. Although explicit incentives explain a substantial portion of the variation in production outcomes relative to that which *could* be explained by incentives (as captured by processor/year fixed effects), there remains considerable variation which might be accounted for by unobserved or implicit incentives. Finally, we control for a quite exhaustive set of factors other than incentive provisions that might conceivably affect expected production outcomes, yet are still left with a substantial amount of unexplained variation.

Paper prepared for presentation at the
American Agricultural Economics Association Meetings,
Montreal, Canada July 27–30, 2003.

Date: May 19, 2003.

We would like to express our thanks to John Welty and the California Tomato Growers Association for making these data available to us. Sarah Baird, Xiangyi Meng, Robert White, and Steven Wu provided valuable research assistance. This research was supported in part by the Gianninini Foundation and by the NRI Competitive Grants Program/USDA award #98-35400-6092, but the views expressed in this article are not endorsed by either of these sponsors.

1. Introduction

The production of processing tomatoes in California is generally governed by a contract between one of a number of processors and individual growers. Tomato quality is a key concern for processors, and is reflected contractually in explicit quality-related performance incentives. 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 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 their effect (both alone and in combination) on the conditional means of measured quality characteristics.

While a number of recent studies have estimated the effect of performance incentives on production outcomes, these studies are mostly limited to comparisons within a single firm between performance under flat wage schedules and performance under some kind of "piece-rate" regime (e.g., Lazear (2000), Paarsch and Shearer (2000)).[1] Ichniowski et al. (1997) use data from a cross section of firms (during a single year), but consider the effect of variation in "human resource management practices," rather than in explicit performance incentives.

The data for our study include include all loads of tomatoes delivered to some 51 processors over a 7 year period in which at least 65 unique types of contracts are employed, and thus represent an opportunity to test for a broad range of incentive effects. After taking account of heterogeneity across growers, tomato varieties, growing regions, years, and delivery months, we estimate an upper bound on the variance in quality outcomes that *could* be due to the provision of incentives; we then see how much variance is actually accounted for by variation in premia explicitly offered in tomato contracts.

Briefly, 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.[2] Although explicit incentives observed in actual contracts explain a substantial portion of the variation in production outcomes relative to that which *could* be explained by

[1] Rather than summarize this literature, we refer the interested reader to Prendergast (1999) who provides a comprehensive overview.

[2] Other authors have examined the response of tomato quality to incentive provisions in contracts using similar data [Alexander et al. (1999); Wu (2001)], but have generally found that incentives provided in these contracts are of minor importance, or have no significant effect on outcomes. Our results suggest that neither of these earlier efforts adequately controlled for observable sources of heterogeneity.

incentives (as captured by processor/year fixed effects), there remains considerable variation which might be accounted for by unobserved or implicit incentives. Finally, we control for a quite exhaustive set of factors other than incentive provisions that might conceivably affect expected production outcomes, yet are still left with a substantial amount of unexplained variation.

2. California Processing Tomato Markets

2.1. **Growers and Processors.** 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). The top portion of Table 1 summarizes the number of growers, processors, and total delivered "loads" in each of the years between 1993–99. The unit of osbservation for our data is a load of tomatoes (slightly less than an acre's production in a typical year), so the number of loads in each year also represents total annual observations.

To identify the influence of incentive provisions on grower behavior (and on expected quality outcomes), we need to observe individual growers delivering tomatoes under more than one type of incentive contract. Provided there is adequate variation in contractual incentives across processors (which we document below), observation of quality outcomes associated with loads delivered by the same grower to different processors provides such an opportunity. The second part of Table 1 presents a simple count of instances where growers deliver loads (of the same variety) to multiple processors. These instances will provide the principal source of identification for our estimation of "incentive effects" in Section 5.

Table 1. Summary Statistics: Growers and Processors

Year	1993	1994	1995	1996	1997	1998	1999
	total number						
Growers	237	276	311	325	287	253	285
Processors	18	22	27	27	24	22	23
Loads	133602	206155	264661	258628	239085	193717	272945
Growers delivering to							
1 processor	145	144	142	139	129	124	145
2 processors	57	56	70	78	72	66	73
3 processors	24	47	52	46	53	36	42
4 processors	5	20	25	34	17	16	11
$\geq$5 processors	6	9	22	28	16	11	14

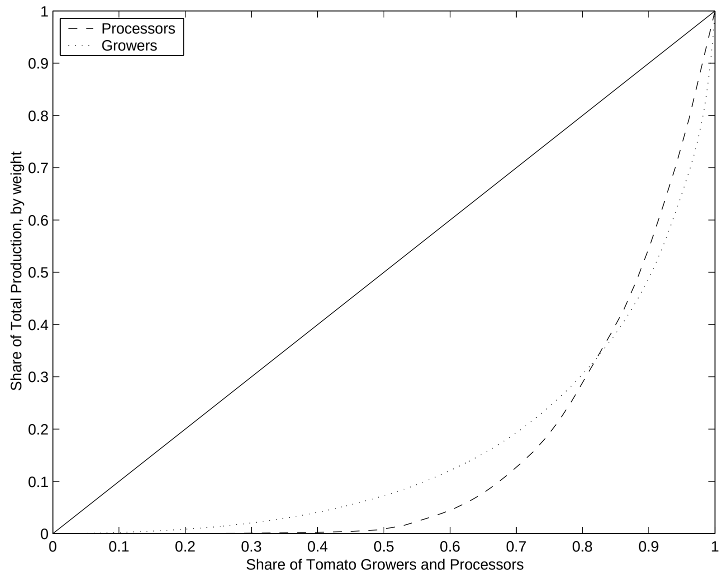

FIGURE 1. Lorenz curves illustrating the distribution of total tomato production (by weight) across growers and processors during the period 1993–99.

Tomato growers and processors vary widely in the size of their operations. Figure 1 displays Lorenz curves for growers and processors and their respective contributions to total industry production over the period 1993–99. There were 533 total growers in these years, and fewer than 10 per cent of these accounted for 41 per cent of total production. Similarly, there were 51 processors in California who bought tomatoes in one or more of the years 1993–99, and half of these accounted for less than 2 per cent of total production.

Among the 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.[3] However, the vast bulk of processing tomatoes are grown by farmers under a contract negotiated before planting. As we describe in greater detail below, the general structure of these contracts is common across processors, but with considerable variation within this structure.

[3]Alexander et al. (1999) use 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 specific kinds of contractual provisions.

2.2. **Institutional Arrangements.** 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% 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 (CTGA members and non-members) must be inspected at a certified PTAB grading station; the standard quality attributes measured for each load include weight, sub-skin color or "comminution" (Comm), the proportion of unripe or green tomatoes (Green) and a measure of sugar content, "soluble solids" (Solids). Also measured are various sorts of damage. These include: Mold, Worms, and extraneous material or "material other than tomatoes" (MOT[4]). Finally, tomatoes that are soft and potentially difficult to processes are classified as "limited use" (LU[5]).

The CTGA and PTAB each play a key role in determining the contractual arrangements that govern the relationship between growers and processors. In particular, quality measures by PTAB help determine the payments made to farmers via processor contracts that condition payment on each measure (or possibly on some subset of measures). 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) that 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.

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

[4]Material other than tomatoes includes "dirt and extraneous material (detached stems, vines, rocks or debris)." (Processing Tomato Advisory Board, `http://www.ptab.org/order.htm`)

[5]A limited use tomato is "i.) whole but has a soft, watery condition under the skin so that more than 25% of the skin is separated from the underlying flesh; ii.) is more than 50% soft and mushy or iii.) is broken completely through the wall so the seed cavity is visible," *ibid.*

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 mentioned 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 in subsequent years. 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.

2.3. **Observed Contracts.** For many of the contracts negotiated by the CTGA, the way quality measurements influence compensation for a given load has a standard form. For future reference it will be useful to characterize this form algebraically. Let $q = (q_1, \ldots, q_m)$ represent a vector of quality measures (which may include measures of both "quality" and "damage"). People in the processing tomato industry draw a distinction between quality characteristics for which growers are rewarded *premia* (in dollars per ton) in contracts versus those for which growers are punished by use of *deducts* (as a percentage of delivered quantity), though some measures are hybrid in the sense that they receive both premia and deducts. Accordingly, letting $\beta_i(q)$ represent premia associated with the realization of measure i, and $\delta_i(q)$ represent the percentage deduct, per-ton compensation is given by

$$w = [1 - \sum_i \delta_i(q)][p + \sum_i \beta_i(q)], \tag{1}$$

where p is a "base price." The functions δ_i and β_i are typically piecewise-linear, and depend on the entire vector of outcomes q because the premium and deduct levels for any given measure may be conditionally dependent on the outcome of one or more *other* measures.[6] Even this standard form permits a great deal of variation, and is typically highly non-linear. Moreover, a considerable proportion of CTGA-negotiated

[6]While this paper does not address the efficiency of contracts, the form taken by compensation is very suggestive. Possible avenues for examining the contract design problem might include a model of multitasking (Holmström and Milgrom (1991); Laffont and Martimort (2002)), in which compensation may take an additively separable form (where only "local incentive compatibility" constraints are binding), or a (possibly simpler) model in which separability across some quality measures follows from the independence of measures conditional on agents' actions, logarithmic utility, and the validity of the "first order approach" (Hueth and Ligon (1999a,b)).

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 is a form of relative performance evaluation).

In practice, the compensation function in equation (1) is implemented with a tabular set of rules that specify intervals for each measure and associated unit premium and deduct levels. We briefly describe one example somewhat arbitrarily chosen from a single processor in 1998. The contract in Table 2 offers a set of "standard deducts" (deductions on these measures are universally provided, though the specific deduct levels may vary from one processor to another), and premiums for MOT, Green, LU, and Comm. Deduct incentives for MOT are significantly higher powered than those for other damage measures; each percent increase in MOT results in an additional three percent deduction from gross weight. Deduct incentives for LU are piecewise, and strictly concave. The LU premium ranges from 0.50 dollars per ton for LU greater or equal to 5 per cent to 5 dollars for LU less than or equal to 0.5 per cent. The maximum LU premium is over 10 percent of the base price (48.5 dollars per ton), and thus represents a substantial economic incentive for producing low LU.[7] Premiums for Comm are conditionally dependent on LU being no more than 4.5 percent, and are highest for intermediate values.

Without knowing something about the conditional (joint) distribution of the quality measures q, it is somewhat difficult to interpret the incentives in Table 2. A slightly more informative representation of this example contract is depicted in Figure 2. Here, we trace out marginal incentives by individually varying the seven quality measures as standard deviations from their respective mean values (over all loads delivered in 1998), and by ordering them so that higher values of each measure are more desirable (with the exception of Comm, which is preferred at intermediate levels for this contract); other characteristics necessary to determine compensation are held fixed at either their means for all loads in 1998, or at their mode where the mean isn't sensible (e.g., for county of origin or date of delivery).

The slope of each line at a given point provides a measure of the local 'power' of incentives. Note that incentives for Mold appear much more highly powered than those for Worms, even though both measures share the same deduct structure in Table 2. This is so because the

[7]The average net weight of a "load" of tomatoes is roughly 25 tons and represents slightly less than an acre's production. Thus, for this particular contract, the maximum potential LU premium per load is roughly 125 dollars.

TABLE 2. Processing tomato contract with an LU, MOT, Green, and Comm "incentive program"; Base Price=$48.50 per net ton.

Measure	Deduction from Gross Weight (%)						
MOT	3×MOT						
Mold	1×Mold						
Worms	1×Worms						
Green	1×Green						
LU (%)	[0,5]		[5.5,8]	[8.5,14]		[14,100]	
deduct	0		1×(LU-5)	1.5×(LU-5)		2×(LU-5)	
	Premium added to Base Price ($/net ton)						
MOT (%)	0						
premium	1.0						
Green (%)	0						
premium	1.5						
LU (%)	[0,0.5]	1	1.5	2	2.5	[3.0,4.5]	[5.0,100]
premium	5.0	4.0	3.75	2.75	1.25	0	-0.5
Comm	[0,19]	20	[21,25]	26	≥ 27		
premium (if LU$\leq$ 4.5)	0	1.0	1.5	1.0	0.0		

(unconditional) standard deviation for Worms across all years is much smaller than that of Mold. Similarly, the MOT deduct incentives in Table 2, which penalize each per cent increase in MOT at three times the penalty for increases in Green, generate nearly identical marginal deduct incentives to those of Green.

So far, we have talked at some length about the general structure of processing tomato contracts, and about the specific structure of one example contract. As noted in the previous section, identification of "incentive effects" (the influence of incentives on behavior) requires adequate variation in contract structures across processors and years. To give some indication of the extent and nature of variation in the structure of these contracts, Table **??** presents the unique set of comminution (as noted earlier, this is a measure of sub-skin color) premia observed across all processors and years. There are a total of 12 unique premium structures for this particular measure across 165 processor/years. A considerable majority of processor/years (144 out of 165) do not offer premium for comminution. Average comminution across all loads and years was roughly 24 with a standard deviation of 2.78. Thus, it's apparent from the incentive structures in Table **??**

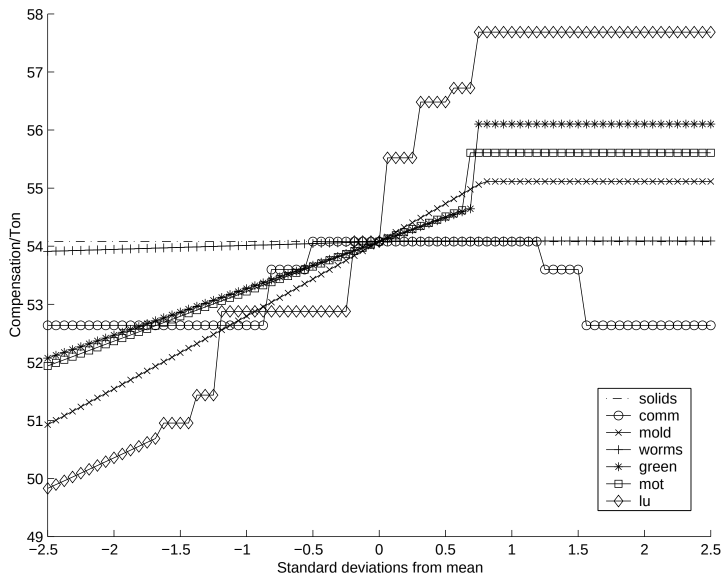

Figure 2. Compensation for the contract in Table 2 evaluated at the mean of each quality measure (and mode grower, variety, location, and date of harvest). Marginal incentives for each measure are evaluated at standard deviations from the relevant mean, holding other measures constant.

that most processors are interested in obtaining *low* levels of comminution (although low comminution is generally preferred, the contract in Table 2 indicates that at least one processor prefers *intermediate* values for Comm). A significant number of processor/years (15) offered comminution incentives with some form of conditional dependence (including the processor associated with the contract in Table 2), and of these, 6 correspond to unique processors.

Incentive structures similarly vary across each of the other quality measures, though to a more or lesser degree. Incentives for LU exhibit the greatest amount of variation with 51 unique structures, followed by MOT (37 unique structures), Solids (14 unique structures), and Green (7 unique structures); there were 2 unique structures observed for Mold and Worms.[8]

[8]For the set of measures on which deducts are assessed (LU, MOT, Green, Mold, Worms), a "unique structure" refers to uniqueness across the combination of premia and deduct provisions. For example, there was only a single instance of a Green premium, but 7 distinct deduct structures for this measure.

One important line of research pursued by Wu (2001) seeks to explain the reasons for the variation observed in contracts—since processors appear to be solving similar problems with their contracts, why is it that they don't all adopt the same contract? Wu's answer is that since different processors use tomatoes for different purposes, they also value tomato attributes differently. For example, processors who make whole tomato products may find it more worthwhile to offer a larger premium for sub-skin color (comminution) than would paste producers. Another possibility might relate differences in the contractual terms offered by various processors to differences in their contracting 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. For present purposes we use observed variation in contract terms to evaluate the effect of contract incentives on expected quality outcomes, and do not explore the reasons for observed variation in contracts. This has the effect of making our results less useful to tomato processors than they might otherwise be—in particular, the results of this paper cannot, on their own, be used to describe what the efficient contract for a given processor would be. We merely describe the effects of variation in contracts on quality outcomes and on the compensation given growers, without making any attempt to describe the varied costs and benefits which would accrue to a processor who adopted a particular contract.

3. Model

In this section, we specify a model that relates equilibrium grower actions (which vary across processors and growers), observed sources of heterogeneity, and unobserved stochastic sources of heterogeneity, to the distribution of quality across different processors.

We begin with a brief description of the environment. Our basic unit of observation is a "load" of tomatoes; we index these n loads by j. Any given load j has a variety of measured characteristics. In particular, the jth load comprises tomatoes of variety $v_j \in \{1, \dots, V\}$, having been grown by a grower $i_j \in \{1, \dots, I\}$ and delivered to processor $\ell_j \in \{1, \dots, L\}$. In addition to these basic characteristics, the jth load will have been harvested in county $d_j \in \{1, \dots, D\}$ in month $m_j \in \{\text{June}, \text{July}, \text{August}, \text{October}\}$ of year $t_j \in \{1, \dots, T\}$. Finally (and critically for our purposes), for each load j we observe a K-vector of quality characteristics q^j.

Growers possess a number of important characteristics. Some of these are assumed to be invariant over time (e.g., industriousness, soil characteristics of the farm operated by grower i, preferences); we denote the invariant grower characteristics of grower i by b_i. Other grower characteristics may vary across time, across load characteristics, or depend on choices made by the grower (e.g., management decisions such as how much fertilizer to use); accordingly, we assume that the grower takes a single set of actions a^{ℓ}_{it} which influences the distribution of quality characteristics for all the tomatoes the grower delivers to processor ℓ.

Not only is the distribution of the vector of quality characteristics assumed to depend on the actions and characteristics of the grower, but also on the time of harvest, location of the field in which the tomatoes are grown, and the variety of tomato comprising the load. Accordingly, we let $G(q|a^{\ell_j}_{i_j}, b_{i_j}, d_j, m_j, t_j, v_j)$ denote the conditional joint distribution of quality characteristics for load j. These conditioning variables are assumed to influence the expected value of the vector q^j according to

$$\text{(2)}\quad \mathrm{E}[q^j|a^{\ell_j}_{i_j,t_j}, b_{i_j}, d_j, m_j, t_j, v_j] = \phi(a^{\ell_j}_{i_j}, b_{i_j}) + \lambda(d_j, m_j, t_j) + \mu(v_j, t_j),$$

where ϕ is an arbitrary vector-valued function of the characteristics and actions of the grower, λ is an arbitrary vector-valued function of the date (month and year) and location where the tomatoes are grown, and μ is an arbitrary vector-valued function of the tomato variety and year.

Of course, in any year a typical grower will produce more than a single load of tomatoes, and so we'll find it convenient to develop a notation which allows us to characterize the joint distribution of quality characteristics for all the loads of tomatoes produced by i in a single year t. We take $\tilde{a}_{it}$ to be a list of the sets of actions for all the processors i delivers to in year t. Similarly, some producers grow tomatoes in more than one county; let $\tilde{d}_{it}$ denote the list of counties to which the grower's loads are delivered. Let $\tilde{m}_{it}$ and $\tilde{v}_{it}$ denote the list of harvest months and varieties grown by grower i in year t.[9] These lists of actions, locations, harvest months and varieties all influence the joint distribution of the quality characteristics of all the loads of tomatoes grown by i in t; call the list of quality

[9]In general, the lengths of these lists will depend on the number of loads of tomatoes produced by the grower, which perhaps ought to be regarded as a random variable. However, in keeping with our focus on quality outcomes rather than quantities, we'll find it convenient to regard the number of loads produced as a number determined by the grower at the beginning of the season. It's worth noting once again that the number of loads to be delivered is negotiated prior to planting.

characteristics for all these loads $\tilde{q}_{it}$, and denote the joint distribution by $\mathcal{G}_{it}(\tilde{q}|\tilde{a}_{it}, b_i, \tilde{d}_{it}, \tilde{m}_{it}, \tilde{v}_{it}) = \prod_{\{j|i_j=i\cap t_j=t\}} G(q^j|a^{\ell_j}_{i_j,t_j}, b_{i_j}, d_j, m_j, t_j, v_j)$. Note that this specification of $\mathcal{G}_{it}$ implies that quality characteristics are conditionally independent across loads.

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 contraints 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; among other things, these contracts condition payment for a given load on realized quality characteristics q. Accordingly, we denote the compensation scheme offered by processor ℓ in year t for delivery of a load of tomatoes having characteristics q as $\pi^\ell_t(q)$. Set against these grower revenues are the costs incurred by a grower having characteristics b who takes actions $\tilde{a}$ affecting the distribution of quality characteristics, which we write as $c(\tilde{a}, b)$.

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

(3)
$$\tilde{a}_{it} = \operatorname*{argmax}_{\tilde{a}} \int U_i \left(\sum_{\{j|i_j=i\}} \pi^{\ell_j}_t(q^j) - c(\tilde{a}, b_i) \right) d\mathcal{G}_{it}(\tilde{q}|\tilde{a}_{it}, b_i, \tilde{d}_{it}, \tilde{m}_{it}, \tilde{v}_{it}).$$

Thus, (3) yields a decision rule which maps contractual provisions and fixed grower characteristics into a set of management decisions taken by each grower. These management decisions in turn influence the distribution of quality and compensation outcomes.

In general, the growers' decision rule (3) makes even management decisions which affect only loads delivered to a given processor depend on the compensation rule offered by other processors. This in turn implies that in designing a contract, any given processor ℓ ought to condition compensation on the quality characteristics of tomatoes delivered to *other* processors. In practice, we don't observe this kind of dependence. Accordingly, let us assume that growers' utility functions are exponential, with $U_i(x) = \sigma_i^{-1} e^{-\sigma_i x}$, where σ_i can be interpreted to be grower i's coefficient of absolute risk aversion (Pratt, 1964). Let us further assume that the growers' cost function takes a linear form in $\tilde{a}$, with $c(\tilde{a}, b) = \sum_{a^\ell \in \tilde{a}} y^\ell_{it}\gamma(b)a^\ell$, where y^ℓ_{it} denotes the number of loads delivered by grower i to processor ℓ in year t (recall that this quantity is negotiated prior to planting). These assumptions suffice to deliver a sort of conditional independence in the actions taken across processors, so that the grower's problem of choosing how to cultivate tomatoes to be delivered to processor ℓ takes the simpler form

(4)
$$a_{it}^{\ell} = \underset{a}{\operatorname{argmax}} -\frac{1}{\sigma_i} e^{\sigma_i y_{it}^{\ell} \gamma(b_i) a} \prod_{\{j \mid i_j = i \cap \ell_j = \ell \cap t_j = t\}} \int \exp[-\sigma_i \pi_t^{\ell}(q^j) dG(q^j | a_{it}^{\ell}, b_i, d_j, m_j, t, v_j).$$

Let $\bar{\pi}_{it}^{\ell}$ denote the *average* compensation grower i receives from processor ℓ for loads delivered in year t. Note that the grower cares only about the *total* compensation he receives. If the number of loads he delivers is small, then he may bear a considerable amount of risk related to variation in realized quality, but as the number of loads he delivers grows large, a law of large numbers implies that the amount of risk faced by the grower will go to zero, and grower i's vector of actions a_{it}^{ℓ} will converge to the value $\hat{a}_{it}^{\ell}$ which solves the matrix equation

$$\gamma(b_i) = \frac{\partial \bar{\pi}_{it}^{\ell}}{\partial \phi(\hat{a}_{it}^{\ell}, b_i)'} \frac{\partial \phi(\hat{a}_{it}^{\ell}, b_i)'}{\partial a}. \tag{5}$$

This rule determining actions amounts to equating the marginal cost of each action to the marginal benefit, given the compensation rule π_{it}^{ℓ} and the influence of actions on expected quality outcomes $\phi(a, b)$.

4. Data

In addition the contracts described in Section 2.3, we have collected the measured load characteristics of each of the over 1.5 million loads of processing tomatoes delivered under these contracts, accounting for roughly 65 per cent of all the processing tomatoes produced in California during the 1993–99 period. Each load of tomatoes was graded at one of 45 grading stations in the state, and then delivered to one of 51 processors. Table 3 summarizes various statistics of these loads (and associated compensation) conditional only on year for three selected years.

On average damaged tomatoes (those which have problems with Mold, MOT, Worms, Green, or LU) comprise roughly 5 per cent of each load of tomatoes. Of this 5 per cent, half of the damaged tomatoes are of limited use. Mold, Green, MOT are the next most important sources of damage, in decreasing order of importance; significant damage from Worms is quite unusual. However, both within and across years, damage from Worms exhibits the greatest variability (as measured by the coefficient of variation), followed by MOT, Mold, Green, and LU. These measures of damage are all commensurate, as each is measured in terms of the damaged proportion of a random sample of tomatoes. The remaining measures, Comm and Solids are not commensurate with these; however, the coefficient of variation of these two quality measures is much smaller than is variation in the damage measures.

TABLE 3. Summary Statistics: Quality and Compensation Outcomes

	1994		1996		1998	
Measure	mean	s.d.	mean	s.d.	mean	s.d.
Comm	23.27	2.76	25.13	2.79	24.48	2.84
LU	2.58	2.45	2.46	2.51	2.03	2.03
MOT	0.33	0.45	0.30	0.43	0.33	0.51
Solids	5.16	0.55	5.19	0.52	5.28	0.49
Green	0.73	0.75	0.76	0.70	1.00	1.41
Mold	1.34	1.59	1.16	1.23	1.81	2.17
Worms	0.01	0.10	0.02	0.11	0.02	0.12
	Premium ($/ton)					
Comm	1.07	1.01	1.29	1.13	1.43	1.28
LU	0.91	0.69	1.07	0.91	1.80	1.31
MOT	0.50	0.68	0.55	0.65	0.63	0.81
Solids	0.74	1.18	1.01	1.69	1.35	1.14
	Deduction ($/ton)					
Green	0.21	0.32	0.21	0.29	0.29	0.52
LU	0.28	0.92	0.29	0.98	0.16	0.67
MOT	0.20	0.39	0.17	0.38	0.22	0.72
Mold	0.33	0.39	0.30	0.32	0.47	0.56
Worms	0.00	0.02	0.00	0.03	0.01	0.03

Mean premia range between 50 cents for MOT in 1994 and 1.8 dollars for LU in 1998. There is considerably more spread among the various premium levels than among the dollar value of deducts. With the exception of Worms (which rarely results in a deduction) each of the deduct measures generally results in a reduction of 20 to 30 cents in per ton compensation. Also, mean premia increased for each measure across the reported years, while there is no apparent trend in the deduct levels.

Table 4 summarizes variation in quality that can be explained by observed sources of heterogeneity other than differences in contract structures. Processing tomatoes are harvested over a roughly five month period, beginning in June and ending in October, starting in the southern part of the state and moving north over the course of the summer. Surprisingly little of the variation observed in quality characteristics is due to location and the time of harvest. The second row of Table 4 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.[10] Time and location explains eight per cent of the variation in measured mold, four per cent of the variation in color (measured by Comm), and somewhat less than three per cent of the variation in LU tomatoes. MOT 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.

	Solids	Worms	Comm.	Green	Mold	MOT	LU
Grower-Year	0.2441	0.0430	0.3014	0.2420	0.2050	0.1184	0.2127
County-Month-Year	0.1228	0.0324	0.2339	0.1360	0.2411	0.0364	0.1278
Variety-Year	0.1980	0.0133	0.2137	0.0786	0.1287	0.0225	0.1511
Processor-Year	0.0640	0.0236	0.1508	0.1079	0.0628	0.0224	0.0733
R^2	0.3746	0.0655	0.4034	0.2909	0.3306	0.1326	0.3242

Table 4. ANOVA Results for Quality Measures. Each of the first four rows reports the proportion of variance in quality measures accounted for by the set of dummy variables described in the first column. The final row reports the R^2 statistic for a least squares regression of each quality measure on all the dummy variables.

Much more variance in quality characteristics is accounted for by information on grower-year. 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

[10]The computation of variance explained is carried out by regressing each quality measure on each set of indicator variables alone, and thus represents an upper bound on the total variation that is *uniquely* explained by each respective set of indicators.

characteristics account for as much as 30 per cent of the variation observed in Comm, 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.

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 Comm, twenty per cent of Solids, fifteen per cent of LU, 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.

Finally, processor and year account for between two and fifteen percent of the variation in observed quality outcomes. In the next section, we argue that the variation in quality outcomes explained by this set of indicator variables represents an upper bound on the amount of variation than can be explained by incentive provisions in contracts.

5. Empirics

Our aim in this paper is to estimate the effects that specific incentive provisions have on the quality characteristics of processing tomatoes. We have extensive data on these quality characteristics, and know from the previous section that the distribution of these characteristics depends on aspects of the environment (weather, soil, tomato variety) as well as on actions taken by the grower.

If we had data on the actions taken by growers, we might find it tempting to regard (2) as the basis of 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 (2) and (3), or the use of instrumental variable techniques.

As we do not in fact observe data related to the actions taken by growers, we are preserved from temptation. In order to focus on the effect of incentives on quality outcomes, we sweep out any (linear) influence of county, month and year or variety and year by defining a pair of operators

$$M_\lambda z = z - \mathrm{Proj}(z|d, m, t)$$

and

$$M_\mu z = z - \mathrm{Proj}(z|v,t).$$

Thus, for example, $M_\lambda q^j$ is equal to the part of quality outcomes q^j which can't be predicted via a linear regression of quality outcomes on a set of county-month-year dummy variables (we have seven years of data; there are 59 counties and six months in which processing tomatoes are sometimes harvested, and so a total of 420 dummy variables). Similarly, we employ a set of 1198 variety-year dummies (there are 394 different varieties delivered in our data, but most varieties aren't delivered every year) to construct the operator M_μ, and apply each of these operators to

$$q^j = \phi(a^{\ell_j}_{i_j,t_j}, b_{i_j}) + \lambda(d_j, m_j, t_j) + \mu(v_j, t_j) + u_j, \tag{6}$$

where u_j is a disturbance term; applying each of these operators and summing over all the loads delivered by i to ℓ at t yields

$$\frac{1}{y^\ell_{it}} \sum_{\{j|(i_j,\ell_j,t_j)=(i,\ell,t)\}} M_\lambda M_\mu q^j = M_\lambda M_\mu \phi(a^\ell_{it}, b_i) + \frac{1}{y^\ell_{it}} \sum_{\{j|(i_j,\ell_j,t_j)=(i,\ell,t)\}} M_\lambda M_\mu u_j,$$

or more compactly,

$$q^\ell_{it} = M_\lambda M_\mu \phi(a^\ell_{it}, b_i) + u^\ell_{it},$$

where $q^\ell_{it} = \frac{1}{y^\ell_{it}} \sum_{\{j|(i_j,\ell_j,t_j)=(i,\ell,t)\}} M_\lambda M_\mu q^j$ and $\frac{1}{y^\ell_{it}} \sum_{\{j|(i_j,\ell_j,t_j)=(i,\ell,t)\}} M_\lambda M_\mu u_j$.

The term $M_\lambda M_\mu \phi(a^\ell_{it}, b_i)$ is still problematic, of course; we don't know the function ϕ, we don't observe its arguments, and we expect that the actions a^ℓ_{it} taken by grower i and the types of growers who contract with processor ℓ are both endogenous. However, we have a model of grower behavior which tells us that grower actions will be a function of both contractual characteristics and grower type b_i. Accordingly, let $f_i(\pi^\ell_{it}) = M_\lambda M_\mu \phi(a(\pi^\ell_{it}, b_i), b_i)$ denote the expected quality characteristics grown by i engendered by the contract π^ℓ_{it}. As described earlier, this contract can be decomposed into terms involving just the base price paid per ton, terms specific to particular quality measures, and a residual, or

$$\pi^\ell_{it} = p^\ell_{it} + \sum_{k=1}^{K} {}_k\pi^\ell_{it} + \xi^\ell_{it}.$$

Substituting this into one of the unknown functions f_i and twice applying the Taylor theorem, we have

(7)

$$f_i(\pi^\ell_{it}) = f_i(\bar{p}_{it}) + \frac{\partial f_i(\bar{p}_{it})}{\partial \pi}(p^\ell_{it} - \bar{p}_{it}) + \sum_{k=1}^{K} \frac{\partial f_i(p^\ell_{it})}{\partial \pi} {}_k\pi^\ell_{it} + \frac{\partial f_i(p^\ell_{it})}{\partial \pi}(\xi^\ell_{it} - \bar{\xi}_{it}) + \zeta^\ell_{it},$$

where $\bar{p}_{it}$ is the average base price offered by the processors delivered to by grower i in year t, and where similarly $\bar{\xi}_{it}$ is the average level of 'extra' incentives offered by these same processors. Finallly, ζ^ℓ_{it} is a vector of Taylor residuals, which will capture any non-linearities in the response of expected quality outcomes to changes in the base price p^ℓ_{it}, quality-measure specific incentives $\{{}_k\pi^\ell_{it}\}$, or in the 'extra' incentives ξ^ℓ_{it}.

Using (7) to substitute into the expression relating grower actions to expected quality outcomes yields the following expression for the expected quality of grower i's year t deliveries to processor ℓ

$$\mathrm{E}[q^\ell_{it} | p^\ell_{it}, \{{}_k\pi^\ell_{it}\}, \xi^\ell_{it}] = \mathrm{E}[f_i(\bar{p}_{it}) | p^\ell_{it}, \{{}_k\pi^\ell_{it}\}, \xi^\ell_{it}] + (p^\ell_{it} - \bar{p}_{it})\mathrm{E}[\frac{\partial f_i(\bar{p}_{it})}{\partial \pi} | p^\ell_{it}, \{{}_k\pi^\ell_{it}\}, \xi^\ell_{it}] + \sum_{k=1}^{K} {}_k\pi^\ell_{it}\mathrm{E}[\frac{\partial f_i(p^\ell_i}{\partial \pi}$$

We let $x^\ell_{it} = [(p^\ell_{it} - \bar{p}_{it})\ {}_1\pi^\ell_{it} \dots {}_K\pi^\ell_{it}\ \xi^\ell_{it}]$. This in turn suggests the reduced form matrix estimating equation

$$q^\ell_{it} = \alpha_{it} + \iota_K x^\ell_{it}\mathbf{B} + \psi\zeta^\ell_{it} + \epsilon^\ell_{it}. \tag{8}$$

Here the α_{it} is a set of fixed effects, which capture variation in $f_i(\bar{p}_{it})$ (which is constant across the processors delivered to by grower i by construction), and ι_K is a column vector of K ones. Remaining variation in q^ℓ_{it} must be due to differences in processors, not differences in growers or years. In particular, note that if grower i delivers to only a single processor ℓ in year t, then the right-hand-side variables of interest in (8) will all take the value zero. If, on the other hand, grower i delivers tomatoes to multiple processors, then these variables will reflect deviations in the contract terms offered by processor ℓ from the mean of the contractual terms offered by all the processors to which i delivers in a given year.

Since the contractual terms found in (8) are all predetermined, if in fact we observed every grower delivering to every processor in every year, we could estimate (8) via least squares. However, no grower delivers to every processor; some matching process between processors and growers determines the number of loads delivered by each grower to each processor in every year. As a consequence, using least squares to estimate (8) directly would provide consistent estimates of the expected effect of the provisions on mean quality outcomes conditional on the assignment of growers to processors, but we're chiefly interested in the unconditional effect of incentives on outcomes.

Accordingly, we formalize the selection problem by using observables to predict the number of loads delivered from each grower to every processor in each year. Per the notation developed above, the number of loads actually delivered by grower i to processor ℓ in year t is denoted by y^{ℓ}_{it}. This quantity must be non-negative, but in the absence of this constraint we imagine that the quantity of tomatoes delivered by i to ℓ at t would be some quantity $\tilde{y}^{\ell}_{it}$, with

$$\tilde{y}^{\ell}_{it} = x^{\ell}_{it}\gamma + z^{\ell}_{it}\delta + v^{\ell}_{it}. \tag{9}$$

Here the vector x^{ℓ}_{it} is a vector of contract characteristics, as above, while z^{ℓ}_{it} is a set of observed processor-grower characteristics which is assumed to be exogenous, such as the distance from the growers' fields to the processing plant (processing tomates are harvested when ripe, and delivery must be quick). We assume that the latent variable $\tilde{y}\ell_{it}$ is observed only when non-negative, with

$$y^{\ell}_{it} = \max(0, \tilde{y}^{\ell}_{it}).$$

We follow Wooldridge (1995) in assuming that v^{ℓ}_{it} is independent of $(x^{\ell}_{it}, z^{\ell}_{it})$, and is distributed $N(0, \sigma_t)$. Note that although we assume normality, we permit arbitrary temporal dependence and heteroskedasticity (e.g., we expect that there may be unexplained serial correlation in the number of loads delivered by i to ℓ). We must also place some structure on the relationship between v^{ℓ}_{it} and ϵ^{ℓ}_{it}—we assume a linear structure governs the conditional mean dependence of these variables, or that there exists a set of mean zero random vectors $\{\alpha^{\ell}_{i}\}$ and a vector ρ so that

$$\mathrm{E}(\epsilon^{\ell}_{it} | \alpha^{\ell}_{i}, x^{\ell}_{i1}, \ldots, x^{\ell}_{iT}, v^{\ell}_{it}) = \alpha^{\ell}_{i} + \rho v^{\ell}_{it}.$$

6. Results

We characterize the complicated set of observed contractual provisions in two ways. In Table 5, we present results from regressing $\Delta\phi^{\ell}_{it}$ on the base price p offered by the processor, on a set of dummy variables indicating the presence of premia or deductions for each quality characteristic, and on the total volume of tomatoes annually received by each processor (a measure of processor size). All processors offer some form of deduct on MOT, LU, worms, green, and mold, and no processor deducts for low soluble solids or high comminution. In contrast, there is substantial variation in the set of measures that are awarded premia. 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 5, 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.

Interpreting results from Table 5, we first note that total annual volume for each processor (measured in millions of tons) is significant in the equations for solids, comminution, 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 proportion of limited use tomatoes.

Given the structure of processing tomato contracts described in (1), 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.

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 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 5 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

	Solids	Worms	Comm.	Green	Mold	MOT	LU
Volume	0.0000*	-0.0000	0.0002*	0.0001*	0.0000	0.0000*	0.0001*
	(8.7522)	(-1.4195)	(17.0295)	(18.1017)	(1.4401)	(3.7732)	(9.0434)
Base Price	-0.0002*	0.0000*	-0.0008*	-0.0002*	0.0001*	0.0001*	0.0000
	(-13.0262)	(5.7822)	(-8.4229)	(-6.6539)	(2.6094)	(3.1745)	(0.1345)
Solids	0.0001	-0.0006*	-0.0803*	-0.0180*	-0.0036	-0.0101*	-0.0544*
	(0.0554)	(-2.3426)	(-14.0904)	(-8.6488)	(-1.0268)	(-9.0395)	(-10.8786)
MOT	-0.0150*	-0.0022*	-0.0249*	-0.0279*	0.0014	-0.0052*	-0.0735*
	(-10.4997)	(-6.3457)	(-3.4119)	(-10.4767)	(0.3084)	(-3.6248)	(-11.4725)
MOT, Solids	0.0432*	0.0000	0.0183*	-0.0193*	-0.0545*	-0.0157*	-0.1780*
	(25.8493)	(0.0747)	(2.1337)	(-6.1673)	(-10.2397)	(-9.3376)	(-23.7139)
LU	0.0275*	-0.0030*	0.0144	-0.0529*	-0.0716*	-0.0157*	0.0121
	(10.0541)	(-4.5200)	(1.0296)	(-10.3482)	(-8.2122)	(-5.7175)	(0.9824)
LU, Solids	0.0465*	-0.0003	-0.2497*	-0.0248*	-0.0189*	-0.0255*	-0.0808*
	(18.0089)	(-0.5377)	(-18.8977)	(-5.1364)	(-2.3021)	(-9.8143)	(-6.9711)
LU, MOT	0.0071*	-0.0014*	-0.1109*	-0.0110*	0.0146*	0.0001	-0.0134*
	(6.6771)	(-5.5486)	(-20.3337)	(-5.5018)	(4.2982)	(0.0718)	(-2.7992)
LU, MOT, Solids	0.0303*	-0.0019*	0.1760*	-0.0404*	-0.0345*	-0.0200*	0.0203
	(12.7454)	(-3.3707)	(14.4889)	(-9.1018)	(-4.5606)	(-8.3786)	(1.9069)
LU, Mold, MOT, Solids	0.0146*	-0.0000	0.1260*	0.0032	-0.0806*	-0.0161*	-0.0861*
	(5.2743)	(-0.0258)	(8.8956)	(0.6236)	(-9.1477)	(-5.7846)	(-6.9336)
Comm, Solids	0.0150*	0.0028*	-0.0444*	-0.0121*	0.0543*	0.0016	-0.2253*
	(5.5289)	(4.3230)	(-3.1953)	(-2.3899)	(6.2810)	(0.5691)	(-18.4800)
Comm, LU	0.0034*	-0.0015*	0.1204*	-0.0339*	-0.0380*	-0.0156*	-0.0333*
	(2.3475)	(-4.4497)	(16.4068)	(-12.6536)	(-8.3240)	(-10.8092)	(-5.1678)
Comm, LU, Solids	0.0094*	-0.0034*	-0.0814*	-0.0392*	-0.0387*	-0.0126*	0.0214*
	(7.4408)	(-11.3665)	(-12.6144)	(-16.6488)	(-9.6456)	(-9.9643)	(3.7859)
Comm, LU, MOT	-0.0175*	-0.0011*	-0.1248*	-0.0228*	-0.0110	-0.0003	-0.1190*
	(-9.4202)	(-2.5125)	(-13.1460)	(-6.5806)	(-1.8684)	(-0.1576)	(-14.2900)
Comm, LU, MOT, Solids	-0.0028	-0.0027*	-0.1357*	-0.0314*	-0.0682*	-0.0039	-0.0595*
	(-1.0834)	(-4.4240)	(-10.3835)	(-6.5718)	(-8.3914)	(-1.5097)	(-5.1932)
Comm, Green, LU, MOT	-0.0682*	0.0035	-0.0225	0.0856*	0.2209*	-0.0172	-0.0571
	(-5.6761)	(1.2254)	(-0.3665)	(3.8124)	(5.7728)	(-1.4212)	(-1.0579)
R^2	0.3706	0.0619	0.4020	0.2867	0.3302	0.1319	0.3191
Relative Efficiency	0.1493	0.0373	0.1659	0.0517	0.0691	0.1433	0.1055

Table 5. 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 4 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.

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 5, 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 5, 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 high-powered incentives for reducing damage, and growers are able to respond effectively for the green and mold measures.

The results in Table 5, while revealing, involve the use of only very crude measures of variation in contracts. We'd like a simple way to characterize contracts which would capture not only the presence of a given sort of incentive, but which would also capture variation in the magnitude of such incentives. In this we are guided by the problem facing the growers who care principally about the expected compensation received under any given contract. We summarize the expected "power" of incentives in two ways. First, for each quality attribute, we compute the difference between expected compensation, and expected compensation after removing incentives for the relevant attribute. This measure of power is a sort of average price offered for the attribute. Second, we compute the difference between expected compensation when quality is increased marginally (five percentile points above the percentile for the mean of each measure), and actual expected compensation. This measure of power gives in indication of the marginal increase in payment the grower can expect from taking actions to marginally improve quality.

Of course, in computing these measure for grower i and processor ℓ, it won't do to use loads delivered by i, as these quantities are endogenous, depending on the actions taken by the grower in response to incentives. Instead, for each grower i and processor ℓ, we compute average incentives using the loads delivered by other growers. Because contractual provisions for any given processor vary across years and often depend on variety, location, and the timing of delivery, we also condition these quantities on tomato variety v, county d, delivery month m, and year t.

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.

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).

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