ESTIMATION OF AN OPTIMAL TOMATO CONTRACT

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ABSTRACT. This paper estimates an agency model of contracts used in California's processing-tomato industry. Model estimation proceeds in three stages. We first estimate growers' stochastic production possibilities, and then, for a given vector of preference parameters, compute an optimal compensation schedule. Finally, we compare computed compensations with actual compensations and choose preference parameters to minimize distance between the two. Assuming perfect competition and risk neutrality for processors, we obtain an estimate of .08 for growers' measure of constant absolute risk aversion (where returns are measured in units of \$100/ton), and find that growers' effort cost is 1.8% of total operating cost. Welfare losses from information constraints are estimated at .59% of mean compensation, and quality measurement improves efficiency (measured as a percentage increase in expected quality) by 1.08%.

1. INTRODUCTION

Theoretical study of contracts has progressed a great deal in recent years. Advances in this area have significantly improved our understanding of the role information constraints play in shaping various kinds of market and non-market institutions. Unfortunately, attempts to empirically test contract theories, and to measure the magnitude of welfare losses arising from information constraints, remain scarce. Moreover, much of the evidence that *has* been accumulated seems inconsistent with the risk and incentives tradeoff present in the standard principal-agent model (Prendergast 1999).

This paper uses data from California's tomato-processing industry to estimate the primitives of an agency model that captures the essential features of contracts between growers and processors in this industry. Unlike most previous empirical work employing agency theory, our data are sufficiently rich to allow for estimation of agents' (stochastic) production possibilities. Using this

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estimated technology, we choose preference parameters—agent risk aversion, and the cost of effort—to compute optimal compensation using the nonlinear program developed by Grossman and Hart (1983). Finally, we perform a global search over feasible parameters to minimize distance between the computed and observed compensation schedules.

In what follows, we briefly describe the tomato contracting environment that is the subject of our investigation. We then present a simple principal-agent model that captures the essential features of this environment. In the subsequent two sections we estimate the primitives of our model and conduct two counter factual experiments: efficiency gains from removal of incentive constraints in the principal's contract design problem, and changes in expected quality when contracts are conditioned on only a single performance measure. The final section concludes.

2. Tomato Contracting

Two important institutions exist in California that mediate exchange between growers and processors. 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 must be inspected at a certified PTAB grading station.

In California, there are 25-30 processors who buy tomatoes in any given year, and each uses a unique contract with its growers. Contracts are based on acreage allocations and correspond to specific plots within each grower's total acreage. For growers who are CTGA members, there is also a "master contract" that governs incentive structures and dispute resolution procedures. Although each processor's contract is unique, all tomato contracts have a similar structure. Compensation is awarded on the number of tons delivered and is adjusted based on the outcome of one or more quality measures. These include (primarily) color, "limited use", soluble solids, and various measures of damage (e.g., %worms, and %mold).

For future reference, it will be useful to represent a typical tomato contract formally. Let y denote gross tons delivered. A piecewise linear function $\phi(d)$ aggregates some vector of damage measures d into a percent "deduct" (this is used to convert y into net tons). A base price b is then awarded based on net tons, in addition to a premium that is computed with a piecewise linear schedule $\beta(q)$ that depends on the outcome of the vector of quality measures q. Compensation w is then given by

$$w = y[1 - \phi(d)][b + \beta(q)].$$

Table 1 displays the deduct and premium schedules for the contract we estimate later in the paper. The contract conditions payment on only a single quality measure (soluble solids). Though the contracts of other processors have a similar structure, they vary widely in the specific deduct and premium parameters used, and in the quality measures that are employed. Interestingly, limited use sometimes shows up as both a quality measure *and* a damage measure (i.e., it enters compensation via $\phi(\cdot)$ and $\beta(\cdot)$). Also, though agricultural contracts seem a near perfect example of a setting where relative performance incentives ought to be observed, they're used explicitly by only a single processor.

TABLE 1. Processing Tomato Contract with Soluble Solids "Incentive Program"; Base Price=$51 per net ton.

Damage Measures	**Deduction** (%) (Multiply integer by percentage in brackets)									
mot[1]	3[0,1]									
lu[2]	0[0,5]		1[5.5,8]		1.5[8.5,14]			2[14,100]		
green	1[0,2]		2[2.5,1]							
mold	1[0,1]									
worms	1[0,1]									
Quality Measure										
soluble solids (%)	[0,5.1]	5.2	5.3	5.4	5.5	5.6	5.7	5.8	5.9	[6.0,100]
premium ($/(net ton))	0	.5	1	1.5	2	2.5	3	3.75	4.5	5.25

[1]Material other than tomatoes. Includes "dirt and extraneous material (detached stems, vines, rocks or debris)".

[2]Limited use. 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."

(source: Processing Tomato Advisory Board. `http://www.ptab.org/order.htm`)

In the next section we briefly present a simple principal-agent model that will provide the basis for our estimation in the subsequent section.

3. MODEL

Our model is of a processor and a single grower, and governs production and exchange of a single "load" of tomatoes. For simplicity, we represent a load of tomatoes in three dimensions: the size of the load $y \in Y \equiv [y_1, \dots, y_{n_y}]$, one minus the fraction of damaged tomatoes $r \in R \equiv [r_1, \dots, r_{n_r}]$ (in Table 1, r is one minus an aggregation of all "deducts"), and some other quality attribute $q \in Q \equiv [q_1, \dots, q_{n_q}]$ (in Table 1, q represents soluble solids). We let

$s \equiv (y, r, q)$ represent the full vector of signals, and define $S \equiv \{(y, r, q) \mid y \in Y, r \in R, q \in Q\}$ to be the set of all possible realizations of s. The notation $s \geq s'$ has the usual componentwise meaning.

The processor is assumed risk neutral and values a load of size y according to some increasing and concave function $V(ry, q)$.

The grower conditions the joint distribution of s with his choice of action $a \in A \equiv [a_1, \ldots, a_{n_a}]$, assumed unobservable to the processor, and other production inputs that for notational simplicity we suppress. The probability of outcome s is denoted by $p(s|a) > 0$ with $\sum_S p(s|a) = 1$ for all $a \in A$. For action a and compensation $\widehat{w}$, grower utility is given by some von Neumann-Morgenstern utility function $\widetilde{U}(a, \widehat{w}) = G(a) + K(a)U(\widehat{w})$ satisfying Assumption A1 in Grossman and Hart (1983). Reservation utility for the grower is denoted by $\overline{U}$.

Denote compensation given a particular outcome s by $\widehat{w}(s)$, and let $u(s) = U(\widehat{w}(s))$. Then for any action a that is implementable, a Pareto optimal contract solves

$$\min_{\{u(s|a) \mid s \in S\}} \sum_S p(s|a)h(u(s|a)) \tag{1}$$

subject to

$$G(a) + K(a) \sum_S p(s|a)u(s|a) \geq \overline{U}$$
$$G(a) + K(a) \sum_S p(s|a)u(s|a) \geq$$
$$G(a') + K(a') \sum_S p(s|a')u(s|a') \text{ for all } a' \in A.$$

where $h \equiv U^{-1}$ (see Grossman and Hart (1983)). Because $U(\cdot)$ is concave, $h(\cdot)$ is convex and problem (1) is a simple nonlinear program with a convex objective function, and a finite number of linear constraints. Let $C(a)$ denote the value of the objective function at the solution for action a. If for some a, there is no feasible solution, then we set $C(a) = -\infty$; such an a is not implementable. The Pareto optimal action a^* is the one that maximizes the expected value of $V(ry, q) - C(a)$, and the optimal wage schedule is obtained by computing $\widehat{w}(s|a^*) = h(u(s|a^*))$.

In the empirical section that follows, we assume the grower chooses between two actions, $A = \{a_L, a_H\}$ with $a_H > a_L$. Assuming the principal wishes to implement a_H, it is straightforward to verify that a solution to problem (1) satisfies

$$h'(u(s|a_H)) = (\lambda + \mu)K(a_H) - \mu K(a_L)\frac{p(s|a_L)}{p(s|a_H)}, \tag{2}$$

where $\lambda \geq 0$ and $\mu \geq 0$ are the Lagrange multipliers for the first and second constraints, respectively. Consider two possible outcomes s and $s' \leq s$ for the grower's vector of signals. Since $h(\cdot)$ is a convex function, the grower receives higher utility in state s if and only if choosing a_H increases the relative likelihood of observing s. That is, a contract will be monotonic if and only if $p(s|a)$ satisfies the monotone likelihood ratio property. We know that the contract w is monotonic, so any attempt to match up predictions from problem (1) with actual compensations must be monotonic.

Given some arbitrary technology $p(\cdot)$, one way to ensure monotonicity is to simply impose it as a constraint. This simply requires an additional set of linear constraints $u(s|a) \geq u(s'|a)$ for $s \geq s'$. Depending on the context, this may or may not be a reasonable thing to do.

Equation (2) makes clear that the grower's compensation is determined entirely by the informational content of the signals in s. In particular, the processor's objective function only determines which action is implemented, and therefore only has an indirect influence on the shape of the optimal compensation schedule.

4. Empirics

In this section we use data on quality outcomes for processing tomato growers to estimate the likelihoods $p(s|a)$, and preference parameters in $\widetilde{U}(a, \widehat{w})$. We then compare the optimal contract computed from problem (1) with the compensation schedule outlined in Table 1.

For simplicity, we assume growers have exponential utility with $\widetilde{U}(a, \widehat{w}) = -e^{(-\rho(\widehat{w}-a))}$, where ρ is the grower's measure of constant absolute risk aversion. To estimate $p(s|a)$ we assume all growers are identical, and that they choose between two actions $a_L = 0$ and $a_H > 0$. We use data collected from a processor who uses quality incentives, and from a processor who does not, and assume the processor using quality incentives induces a_H for growers delivering under her contract. We interpret a_H as the extra (effort) cost a grower incurs when producing under a contract with quality incentives.

4.1. **Technology Estimation.**

Unfortunately, our data do not include information about y. We therefore treat y as fixed, and focus on the joint distribution of r and q. Figure 1 displays estimated marginal quality distributions for growers delivering tomatoes under the contract in Table 1 and for growers delivering to processors who offer an identical "deduct" schedule, but no soluble solids incentives. We denote the marginal distribution for r by $p(r|a)$, and similarly for q. Quality incentives on q induce the expected shift in its

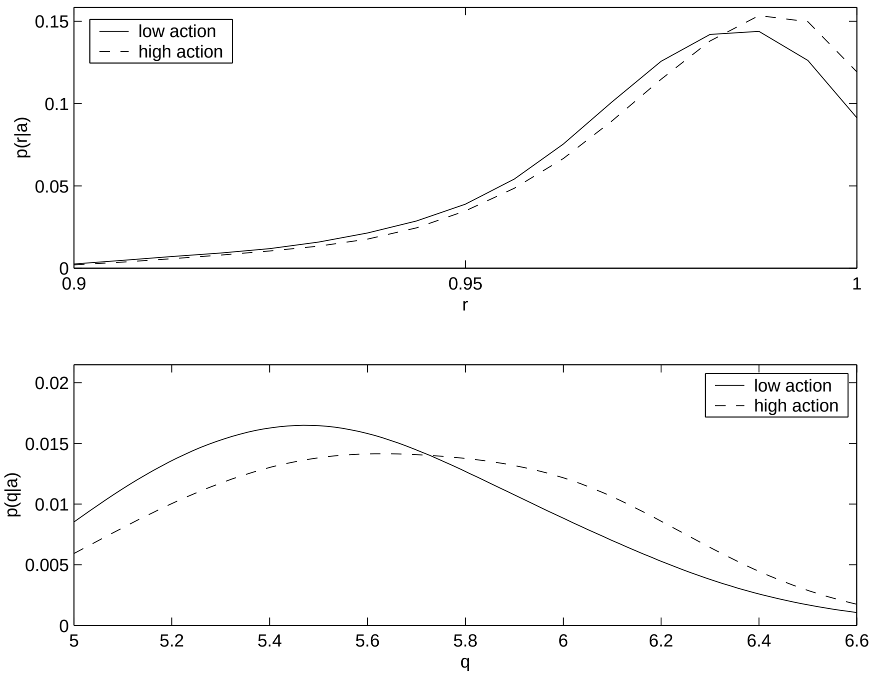

FIGURE 1. Estimated Marginal Distributions for r and q.

marginal distribution, but also induce higher average r. This is not surprising given the structure of w: the expected return from higher r is greater for higher q. Figure 2 displays the estimated joint distribution of r and q for loads delivered to the processor who uses quality incentives.

From the previous section, we know that likelihood ratios are critical for determining the optimal compensation schedule. Denote the conditional likelihood ratio of r given some q by $L(r|q) = p(r, q|a_L)/p(r, q|a_H)$, and similarly for q. Figure 3 presents these conditional likelihood ratios. As is visually apparent from the figure, the likelihood ratios associated with our estimated technology are not everywhere monotonic. Also, r seems to be more informative since its conditional likelihood has greater variance (Kim 1995). It's noteworthy that *all* processors use r in their contracts, while only some processors use q.

4.2. **Contract Estimation.** With an estimated technology in hand, we can now proceed to solve problem (1) for our chosen parameterization of grower preferences. We have three free parameters in our model: the grower's measure of constant absolute risk aversion ρ, the cost of high effort a_H, and the grower's reservation utility $\overline{U}$. Though in principal these three parameters can be estimated jointly, in practice it is difficult to separately identify $\overline{U}$ and a_H. Both act on the grower's participation constraint in a similar fashion. We therefore set reservation utility at 0.96, which is approximately equal to

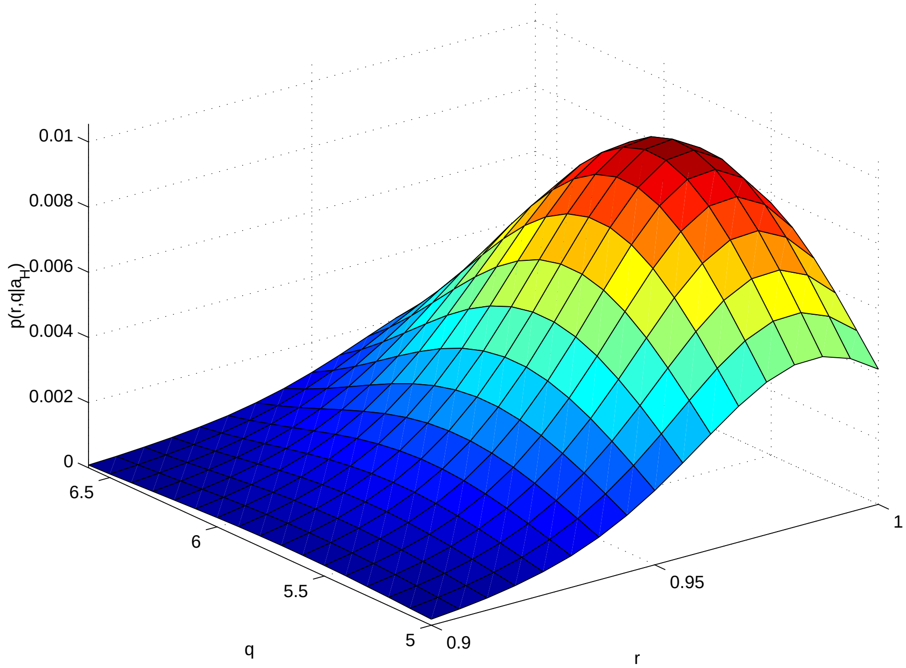

FIGURE 2. Estimated Joint Distribution for r and q, $a = a_H$.

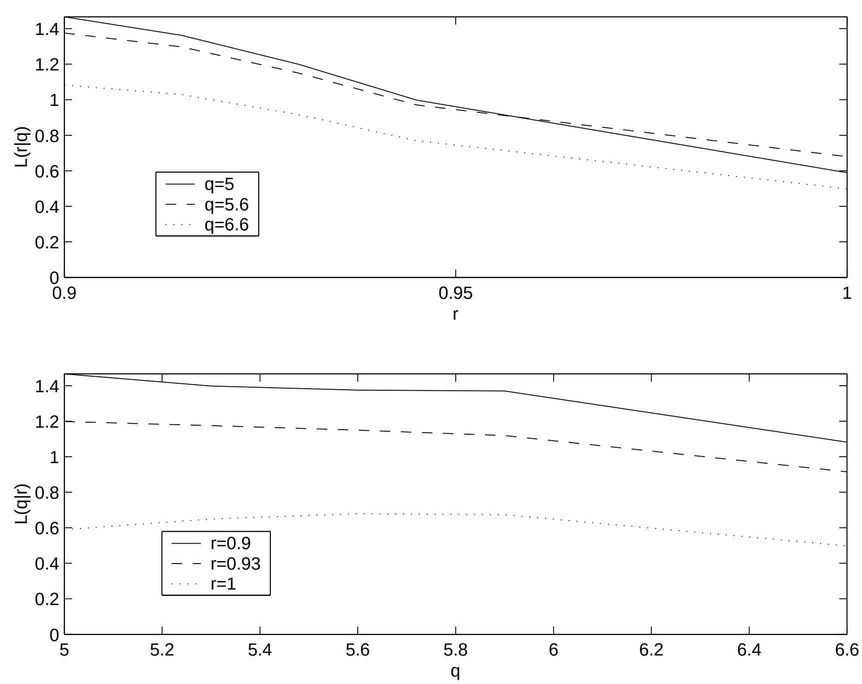

FIGURE 3. Estimated Conditional Likelihood Ratios for r and q.

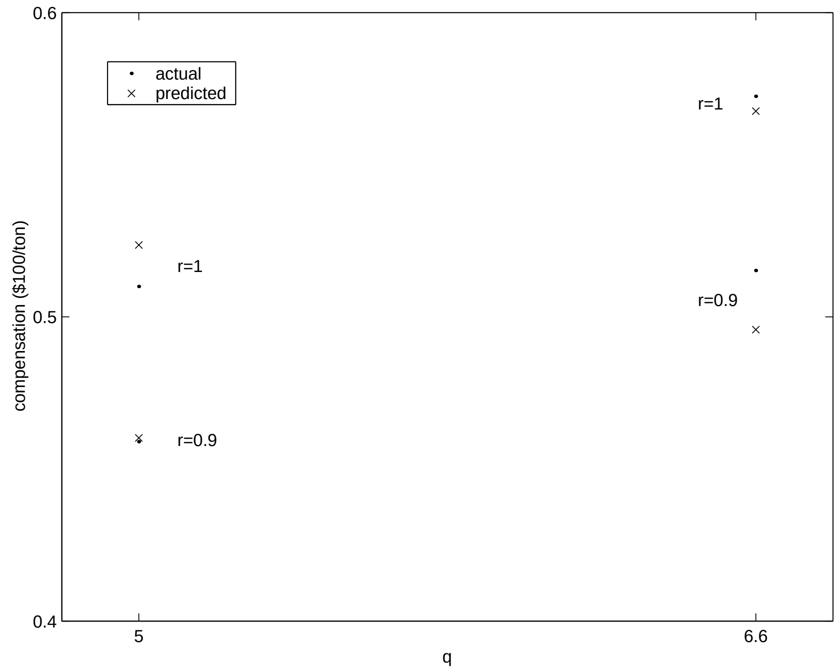

FIGURE 4. Actual and Predicted Compensations, $\widehat{\rho} = .0797$ and $\widehat{a}_H = .0059$.

expected utility obtained under the no-incentives contract for a grower with $\rho = .08$.

In our sample $n_r = 31$ and $n_q = 17$. This makes 527 possible outcome states. Solving problem (1) for this many variables is not practicable. We therefore begin with only two outcomes for each quality measure, and then increase the number of possible outcomes to evaluate the sensitivity of our estimates to grid spacing. Because we don't have information on y, w is compensation per gross ton. We put units in \$100 per gross ton. Figure 4 displays actual and predicted compensations for $\widehat{\rho} = .0797$ and $\widehat{a}_H = .0059$. This is the parameter pair that minimizes the mean squared error between the two compensation schedules given by

$$\frac{1}{n_r n_q} \sum_R \sum_Q [w(r,q) - \widehat{w}(r,q)]^2.$$

After some initial experimentation, parameter estimates were obtained by searching over an equally space grid of 100 values for each parameter ranging from [.07,.09] for ρ and [.004,0.2] for a_H.

Evaluating the magnitude of our estimate for the grower's measure of constant absolute risk aversion is difficult. Few studies have attempted estimates of this coefficient. Nevertheless, an individual with a coefficient of absolute risk aversion equal to .0797 would be willing to accept \$8.66 in return for an even odds gamble that offers an expected return of $50. We will come back to the magnitude of this parameter in the next section when we evaluate welfare losses from private information. Our estimate of effort cost translates into approximately $.60 per ton. Average yields for processing tomato growers are 35 tons per acre, so estimated effort cost per acre is approximately $21. This is roughly 1.8 percent of total operating costs for a typical processing tomato grower (May et al. 2001).

Table 2 reports parameter estimates when we use a finer grid for our outcome states. Our estimate of a_H is somewhat variable, but in general the parameter estimates do not seem very sensitive to grid spacing.

TABLE 2. Estimation Results and Gridsize

	Unconstrained			**Monotonic**		
Gridsize	$\widehat{\rho}$	$\widehat{a}_H$	mse $(\times 10^{-4})$	$\widehat{\rho}$	$\widehat{a}_H$	mse $(\times 10^{-4})$
2	.08	.0051	5.03			
3	.08	.0038	2.58	.08	.0051	1.81
4	.08	.0042	1.99			
5	.08	.0049	2.56	.08	.0049	3.50

Figure 5 displays predicted and actual compensation schedules for a grid with four possible outcomes for each quality measure. As in Figure 4, the model does well predicting compensation when both r and q are low, and when they are both high. The model does less well in intermediate ranges. Perhaps an alternative parameterization of grower preferences could perform better. Also, estimation of the technology $p(\cdot)$ could be carried out jointly with estimation of preferences. In any case, given that the model is unable to more closely match actual compensation, it seems that some aspect of the parameterization we choose is misspecified. An alternative interpretation is that some type of "transaction cost" limits the processor's use of an optimal contract. Ferrall and Shearer (1999) adopt this interpretation and measure the magnitude of these transaction costs by computing the difference between expected surplus under optimal and actual contracts.

5. Agency Costs and Quality Measurement

Having estimated our model, it's possible to carry a number of interesting counter factual exercises. We report the outcome of two such exercises in this section.

5.1. **Agency Costs.** Private information constrains the set of contracts that are feasible. In particular, a full information contract in the environment we consider would not expose the grower to any risk. Using the parameter estimates obtained when $n_r = n_q = 4$, the grower would receive $.51 with

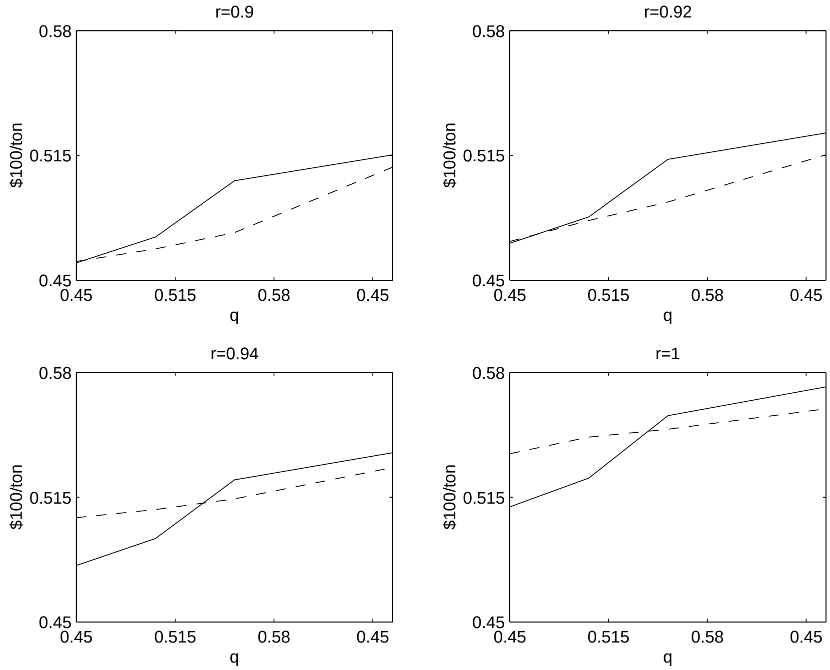

FIGURE 5. Actual (solid line) and Predicted (dashed line) Compensations, $\widehat{\rho} = .08$ and $\widehat{a}_H = .0052$.

certainty. The grower obtains the same expected utility under both the full and private information contracts. The welfare cost of private information is therefore given by the grower's risk premium under the private information contract, and this exactly equals the difference in expected compensation under the two contracts. For $\overline{U} = -.96$ and $\rho = .08$, full information compensation is .5103. Expected compensation under the private information contract is .5155, yielding a welfare cost of \$.0052/ton. This yields a small, almost insignificant, welfare cost from private information of \$55,640 for the entire industry (total production in 1998 was 10.7 million tons).

There are two reasons why our estimate of this welfare cost represents an *extreme* lower bound. First, we've assumed there are only two actions: assuming the high action is implemented under both the full and private information contracts, there is no efficiency loss from private information in our estimate. Losses are only due to the risk that's imposed on growers in the private information contract. Second, to simplify estimation of our model, we ignored and important part of the actual compensation schedule: the part where growers get *no* compensation because a load is rejected. Including this possibility adds substantial additional risk to growers' compensation. As a rough indication of how this might affect our estimate of welfare cost, suppose that growers face a 10% chance of having any load rejected. Total operating costs for a load are roughly \$36/ton, which a grower has to pay regardless of whether his load is rejected. Adding this amount (measured in units of \$100) to our computed private information compensation schedule, and normalizing $p(r, q|a)$ to include a 10 percent chance of rejection, an additional .086 would have to paid to achieve an expected utility of $-.96$. Adding this to our original estimate yields a total welfare cost of .0912, which amounts to an industry wide cost of \$975,840. Though extremely rough, this estimate is suggestive of the possible increase in estimates of welfare costs from private information when extreme penalties (that wouldn't be necessary under full information) are considered.

5.2. **Quality Measurement.** Performance measurement can be an extremely costly undertaking. In the processing tomato industry, growers and processors combined pay roughly \$.30/ton of tomatoes to PTAB (the charge is split evenly between the two parties and is assessed on a per-load basis), amounting to over \$2 million dollars per year. With our estimated model we can evaluate quality improvements that result from this expenditure. One way to do this is simply by measuring the increase in expected quality that results when incentives are present. In our model, quality outcomes under the low action a_L are obtained when there is no performance measurement with respect to q. For this action, $E(q|a_L) = 6.204$, and for the high action $E(q|a_H) = 6.271$, resulting in a 1.08% increase. Similarly, r increases by .5497% from $E(r|a_L) = .9263$ to $E(r|a_H) = .9314$. These percentage increases seem small, which means (given the expenditures on quality measurement noted above) that small increases in quality must yield substantial benefit.

6. Conclusions

This paper estimates an agency model of contracting in California's processing tomato industry. Quality outcomes for growers under contract are used to estimate outcome-state probabilities under two contracts: one that uses an explicit set of quality incentives for soluble solids, and another that does not. We presume that these two contracts implement different grower "actions" and use the ratio of our estimated likelihoods as an estimate of the likelihood ratio that appears in our agency model. We then use the nonlinear program developed by Grossman and Hart (1983) to compute an optimal contract assuming constant absolute risk aversion for growers. We jointly estimate growers' risk aversion and the cost of high effort by minimizing distance between computed and actual compensation schedules.

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