

Anatomy of a Contract Change:

Online Appendix

Rajshri Jayaraman, Debraj Ray and Francis de Véricourt

August 2015

This Online Appendix contains analysis, tables and figures that complement the main text. Section O.1 explains why employers might rationally flatten incentive payments in response to an increase in the government-mandated daily wage. Section O.2 presents data showing that each gang is likely to have exclusive access to a pre-assigned set of fields. Section O.3 contains additional figures. Figure O.3 shows kernel densities and scatter plots for the average daily output of workers in Month 0 and Month 1, using as counterfactuals both the study plantation in the year before the contract change, and the control plantation in 2008. Figure O.4 depicts kernel density and scatter plot estimates for the average daily output of workers disaggregated by hand and shears. Figure O.5 depicts kernel densities and scatter plots analogous to those in Figure 3 in the main text, but for computed residuals rather than output. Figure O.6 repeats the same exercise, but using the Month 0 baseline. Figure O.7 depicts output kernel densities disaggregated by permanent and temporary workers using a Month 0 baseline. Section O.4 contains additional tables. Table O.1 provides estimates of first and double difference in worker output across the contract change, but using Month 0 as the baseline. Tables O.2 and O.3 respectively furnish the D -statistics and mean differences that were used to create Figure A3 in the Appendix of the main text. Table O.4 provides p -values corresponding to the mean differences in Table O.3.

O.1. OPTIMALLY CHOSEN PIECE RATES IN RESPONSE TO MANDATED FIXED WAGES

The purpose of this section is to describe how incentive piece rates might be chosen as a best response by an employer when the government mandates that a certain minimum has to be paid out in terms of fixed wages. Our goal is to explore the statement made by employers that piece rates were reduced to save on costs after the minimum baseline wage was hiked by legislation.

O.1.1. **Instruments.** Suppose that an employer has two instruments at his disposal for eliciting effort. He can pay incentive piece rates, or he can use direct supervision. Assume that the stock of supervisors is given and the outlay to them is fixed. But there are additional non-pecuniary costs that come from “supervising the supervisors”: in essence, from making sure that they work hard to ensure that workers are putting in effort. To achieve this, the employer may now have to visit the plantation on a regular basis, perform random audits, and more generally follow up with the supervisors he has hired to make sure they are doing their job. In line with the empirical findings in the main text, these are the alternative instruments that we consider. Both are costly, but in different ways.

O.1.2. Reactions to a Changed Baseline Wage. Our interest is in seeing how the above mix of instruments is affected when there is a mandated change in the baseline wage paid to workers. There are two possible pathways. The first works through income effects for the worker. When the utility function defined on worker income is strictly concave, an increase in the baseline wage lowers the effort for any given incentive scheme. Under further assumptions on the utility function, it will also lower the *marginal* responsiveness of effort to incentives. Faced with this lowered sensitivity to piece rates, employers will flatten incentives.

However, this was not the stated reason for the flattening of piece rates in the plantation we study, and it will not be our focus here. We were told by the employers that cost outlays had become too high, so they cut back on the incentive scheme *despite* the knowledge that such schemes could continue to be valuable. In the model we consider below, we focus on this particular effect, and in order to remove the income effect, we assume, as in our structural estimation, that worker utility is linear in income. What we do allow for is the possibility that higher pecuniary costs have nonlinear effects on employers, perhaps because of missing or imperfect credit markets.

O.1.3. Pecuniary Incentives and Supervision. Following the main text, then, a worker has a payoff function given by

$$w(y) - \theta c(y) - p(y).$$

The term $w(y)$ is total income from plucking y , generated by the fixed wage f given by law, and some nonnegative *reward function* $R(y)$, so that

$$w(y) = f + R(y).$$

The term $c(y)$ is a cost function for plucked output y , and θ is a cost shock. Finally, $p(y)$ is some nonincreasing *penalty function*, generated by supervisory effort, typically bounded above by some legal maximum. As an example, the plantation could set some minimum standard s and punish defectors below by some penalty function L that depends on the shortfall from s , so that

$$p(y) = L(s - y).$$

At the same time, $R(y)$ could be some piece rate function that kicks in above s ; for instance,

$$R(y) = r \max\{y - s, 0\},$$

in the case of a single piece rate r .

In what follows, we shall assume that the total number of supervisors and their pecuniary compensation are given, but that the plantation employers must exert costly effort in order to make sure the supervisors are doing their job. In its most abstract form, the effort cost to the employers is given by some function $D(p)$, where p is the penalty function that the employers wish to devise. For instance, if p is given by

$$(o.1) \quad p(y) = b \max\{s - y, 0\},$$

then $D(p)$ will typically depend positively on both the value of s and b . It will depend positively on s because supervisors will now have to watch out for a larger range of behaviors, and it will depend positively on b because a penalty can be inflicted only if the supervisors are doing their jobs. We presume that a zero penalty can be imposed at zero cost; that is, $D(p) = 0$ if $p(y) = 0$ for all y .

To summarize, the pecuniary return that the plantation obtains from a worker who has produced y is given by

$$y - R(y) - f$$

while at the same time it incurs a cost of $D(p)$ to implement a desired penalty function p .

O.1.4. The Plantation Owner's Optimization Problem. Faced with a pair of reward and penalty functions, a worker with cost shock θ will choose an output $y(\theta)$ to maximize

$$(o.2) \quad R(y) - \theta c(y) - p(y) + f.$$

With this knowledge in mind, the plantation will choose reward and penalty functions to maximize

$$\pi \left(\int [y(\theta) - R(y(\theta)) - f] dG(\theta) \right) - D(p)$$

where π is a strictly increasing and concave payoff defined on pecuniary returns, and D as already explained is the disutility suffered by plantation owners in their attempt to implement the penalty function p .

Notice that D is a function and we have imposed practically no structure on it except the end-point condition that the penalty $p(y) = 0$ for all y can be imposed at zero cost. We will need a bit more. An ϵ -neighborhood of a penalty function p is the set of all penalty functions q such that $|q(y) - p(y)| \leq \epsilon$ for all y . We will assume that the choice of penalty functions is *malleable* in the sense that if $D(p) = d$ and $d' > d$ is a new "supervision budget," then there exists $\epsilon > 0$ such that every penalty function w in the ϵ -neighborhood of p can be achieved at cost no higher than d' .

This assumption allows enough flexibility for our purposes as the supervisory budget is changed. For instance, if employers are willing to spend more effort in monitoring their supervisors (higher d), then they can increase the slope of their penalty; that is, the value b in the linear example described by (o.1). (This is, of course subject to the condition that the legal maximum, if any, cannot be exceeded.) Or, following up on (o.1) again, they can raise the standard s and "shift" the penalty to start from that higher threshold. All this can be built up, bit by bit using the malleability condition, starting from the zero penalty function which is always available for free.

O.1.5. The Interaction of Supervision and Pecuniary Reward. Notice from (o.2) that for any realization of the shock θ , the worker's choice of output only depends on the "net reward function," given by

$$\Gamma(y) \equiv R(y) - p(y).$$

Moreover, given the linearity of the worker's utility function in income, the value of $\Gamma(0)$ does not matter for worker incentives, just the "shape" of Γ . To solve an artificial but useful benchmark, set $\Gamma(0) = 0$ and choose the function $\Gamma(y)$ to maximize

$$\int [y(\theta) - \Gamma(y(\theta))] dG(\theta)$$

subject to the constraint that $y(\theta)$ maximizes

$$\Gamma(y) - \theta c(y)$$

for each θ . Let Γ^* solve this problem. Notice that this is exactly the reward function that the plantation will choose if it spends nothing on supervision ($D = 0$). That is true irrespective of the shape

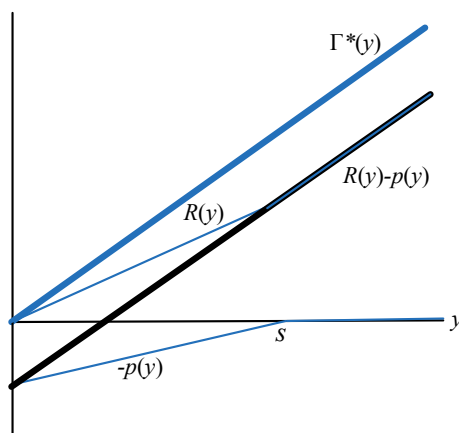


Figure O.1. REWARDS AND PENALTIES THAT SUM TO Γ^* .

of the payoff function π , as long as it is strictly increasing. More generally, if some expenditure on supervision already generates a penalty function $p(y)$, the plantation will set up a reward function $R(y)$ to “account for the remainder” of Γ^* ; i.e., it will make sure that the shape of $R(y) - p(y)$ is exactly the same as that of $\Gamma^*(y)$ (leaving out the intercept term). Now this will not always be possible if the penalty function is chosen arbitrarily (after all, R is restricted to be nonnegative¹), but it will always be possible if the penalty function is carefully chosen, given the supervision budget. Specifically, the malleability assumption will always permit us to choose a penalty function with the property that

$$(o.3) \quad p(0) - p(y) \leq \Gamma^*(y),$$

for all y , and in this case a nonnegative reward function can be always chosen to “make up” for the rest of Γ^* ; i.e., so that for all y ,

$$(o.4) \quad R(y) - p(y) + p(0) = \Gamma^*(y).$$

For instance, if the optimal choice of $\Gamma^*(y)$ is some linear reward λy , the plantation can choose, depending on the supervision effort D , a penalty function that sets a standard s and a penalty of $b \leq \lambda$ for dropping below the standard.² Then R will simply have a slope of $\lambda - b$ up to the standard s and a slope of λ thereafter. The two functions together “add up” to a translate of Γ^* ; see Figure O.1.

This discussion tells us that if the “effort budget” for supervision is tentatively fixed at some d , then incentive piece rates diminish as d increases. For any feasible penalty function p satisfying (o.3), (o.4) tells us that

$$R(y) = \Gamma^*(y) - [p(0) - p(y)]$$

¹For instance, suppose that Γ^* is linear but the penalty function is some step function, with penalties abruptly falling to zero after a threshold. It may not be possible to design any R satisfying the nonnegativity condition such that $R(y) - p(y) = \Gamma^*(y)$ for all y .

²On the other hand, following up on Footnote 1, if $b > \lambda$, then the condition (o.3) is violated and the condition (o.4) will not hold in that case. But that cannot be an overall optimum in which both the penalty function and the reward function are deliberately and optimally chosen.

and so, recognizing that the plantation would like to minimize pecuniary costs $\int R(y(\theta))dG(\theta)$ subject to arriving at the overall reward scheme Γ^* , the plantation seeks to maximize

$$(o.5) \quad \int [p(0) - p(y(\theta))]dG(\theta)$$

by choosing penalty scheme $p(y)$, subject to the conditions (o.3) as well as $D(p) \leq d$. When d increases, the malleability assumption tells us that the integral in (o.5) can be unambiguously increased (except for the case in which $\Gamma^*(y)$ already equals $p(0) - p(y)$ for all y , in which case it is unchanged). That means that incentive piece rate expenditures $\int R(y(\theta))dG(\theta)$ must fall. We use this observation in the next subsection to complete our argument.

O.1.6. The Consequences of an Increased Baseline Wage. We now complete the argument by considering an increase in the baseline wage from f to f' , where $f' > f$.

PROPOSITION O.1. *Suppose that the mandated fixed wage increases. Then supervision expenditures weakly rise, and incentive piece rate expenditures weakly fall.*

Proof. Denote by d and d' the optimally chosen supervision expenditures under f and f' , and by x and x' the gross pecuniary incomes before subtracting the baseline wages. Underlying these are reward and penalty schemes as described in the previous subsections, but we do not need to keep track of these explicitly. All we note is that switching the reward and penalty schemes across the two situations, it is *feasible* to obtain the pecuniary income x' under f and x under f' ; this follows from the assumed linearity of worker utilities in income. Because (x, d) is optimal under f , we see that

$$(o.6) \quad \pi(x - f) - d \geq \pi(x' - f) - d',$$

and because (x', d') is optimal under f' ,

$$(o.7) \quad \pi(x' - f') - d' \geq \pi(x - f') - d.$$

Adding equations (o.6) and (o.7) and transposing terms, we must conclude that

$$(o.8) \quad \pi(x - f) - \pi(x' - f) \geq \pi(x - f') - \pi(x' - f').$$

We first claim that if $f' > f$, then $x' \geq x$. Suppose not. Then $x' < x$. But then by concavity, $\pi(x - z) - \pi(x' - z)$ is decreasing in the variable z . But this property is contradicted by (o.8), because $f' > f$. Therefore $x' \geq x$, as claimed.

We are now in a position to claim that $d' \geq d$. Suppose not; then $d' < d$. But then, using $x' \geq x$, we have

$$\pi(x' - f) - d' > \pi(x - f) - d$$

simply by virtue of the fact that π is increasing. That contradicts (o.6). Therefore the claim is true and $d' \geq d$. By the argument in Section O.1.5, we see that incentive payments must weakly fall, which completes the proof. \square

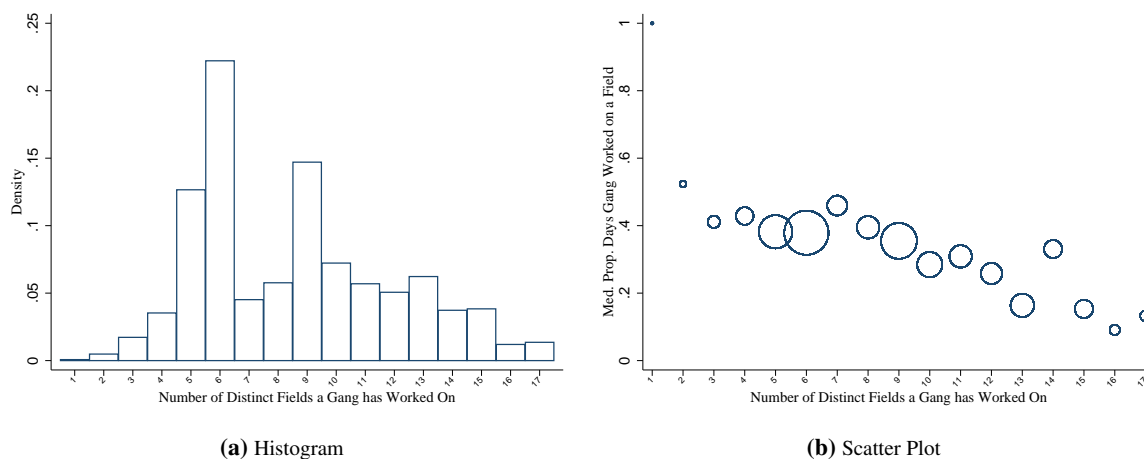


Figure O.2. Gangs on Fields. *Notes.* This figure presents data at the gang-field-day level for the Treatment Plantation in 2008. Panel (a) is a histogram depicting the proportion of gangs that has worked on x distinct fields. Panel b presents the number of distinct fields on the x-axis, and for each x-axis value, the median proportion of days gangs spend on each field. Bubbles are proportional to the number of gangs.

O.2. GANG ASSIGNMENT TO FIELDS

In this Section we provide corroboratory evidence that each gang has exclusive access to a given set of fields. We focus on the 2008 season, where we have 124 daily observations with 91 gangs covering 211 fields. (The pattern is almost identical in 2007.) Gangs are pre-assigned to fields at the beginning of the season, with minor weather- and absenteeism-related adjustments. Fields are of different sizes, so workers may spend several days on the same field; may pluck 2 or more fields on a given day; and more than one gang may be assigned to the same field, even on the same day.

Within a field, workers are always assigned to the same row(s) of bushes. This internalizes the costs of over- or under-plucking provided workers have exclusive access to a given row. Unfortunately, we do not have worker-row-level observations to verify this. Nevertheless, by observing the distribution of gangs over fields, we can put some bounds on how likely it is that gangs do, indeed, have exclusive access to a set of fields. On average, gangs pluck 1.34 fields a day: 67% of pluck 1 field a day, 32% pluck 2 and 1% pluck 3. If gangs rotated through all the fields in the plantation, we should observe them in about 157 distinct fields, spending less than 1% of their time on any given field.

Figure O.2 shows that this is clearly not the case. It depicts the number of distinct fields a gang has worked on (x-axis) and, for each of these values, the median proportion of days a gang has spent on each field (y-axis). Bubbles are proportional to the number of gangs. The number of distinct fields a gang plucks ranges from 1 to 17. The relationship between the time spent on each field and the number of distinct fields plucked is negative. So while it is possible that field and row assignments across different gangs overlap, the fact that some gangs pluck a larger number of distinct fields is more likely to reflect the small size of the fields on the right of the scatter plot relative to the left.

On average, gangs work on only 8.6 distinct fields and approximately 85% of gangs have plucked 12 or fewer (see Panel a). On average, they spend 35% of their time on a given field (see Panel b).

This is strikingly consistent with work organization in which gangs are assigned to an exclusive set of fields, and these fields were plucked every 5 to 7 days (Hall, 2000), in which case we should observe them in $8.5 (= 5 \times \frac{211}{91 \times 1.34})$ to $12 (= 7 \times \frac{211}{91 \times 1.34})$ distinct fields.

O.3. ADDITIONAL FIGURES

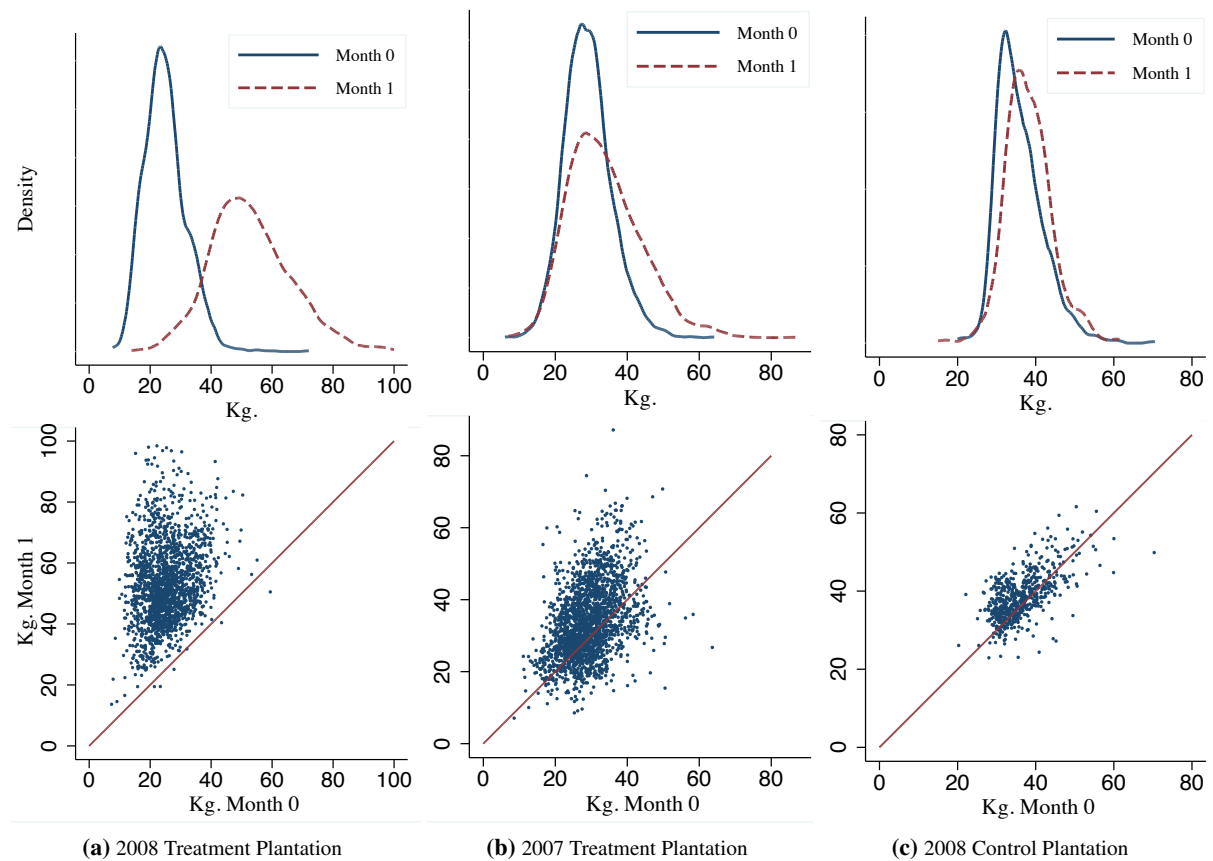


Figure O.3. Kernel Density and Scatter Plots: Average Daily Output. *Notes.* The top three panels of this figure depicts kernel density estimates for the average daily output of workers in Month 0 (solid line) and Month 1 (dashed line). The bottom three scatter plot depict average daily output per worker in Month 0 (x-axis) and Month 1 (y-axis). Each dot represents an individual worker. The solid line is drawn at 45° . Panel (a) corresponds to the study plantation in the year of the contract change, Panel (b) to the study plantation in the year before the contract change, and Panel (c) to the control plantation in the year the contract change took place. Densities are calculated using an Epanechnikov kernel.

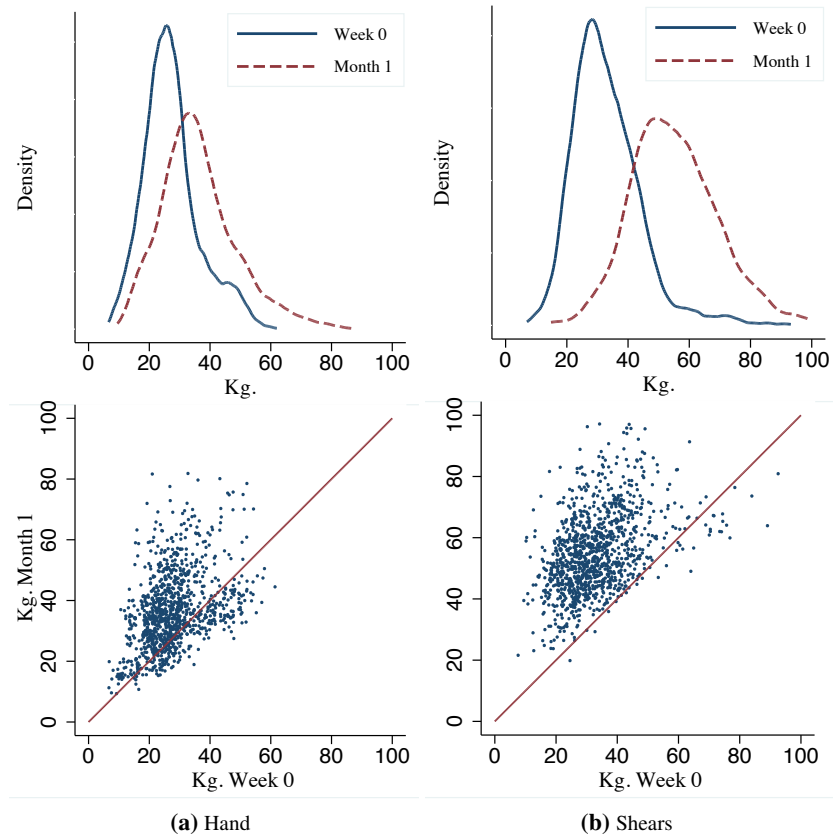


Figure O.4. Kernel Density and Scatter Plots: Average Daily Output Disaggregated by Hand and Shears.
Notes. This figure depicts kernel density and scatter plot estimates of workers' average daily output analogous to Panel (a) in Figure 3 of the main text, but disaggregated by hand (Panel a) and shears (Panel b).

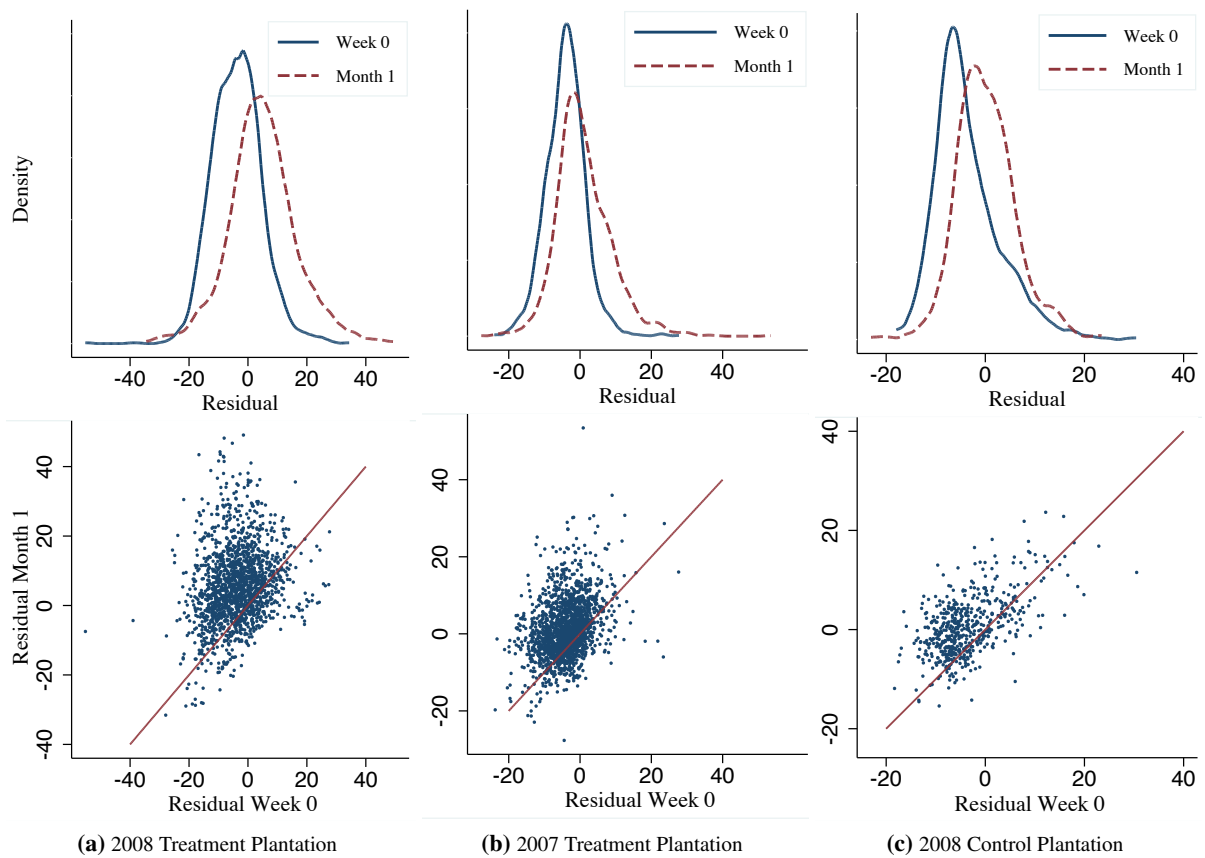


Figure O.5. Kernel Density and Scatter Plots: Average Daily Residual. *Notes.* This figure depicts kernel density estimates and worker-specific scatter plots analogous to those in Figure 3 of the main text, but for residuals obtained after controlling for rainfall, plucking method and field type.

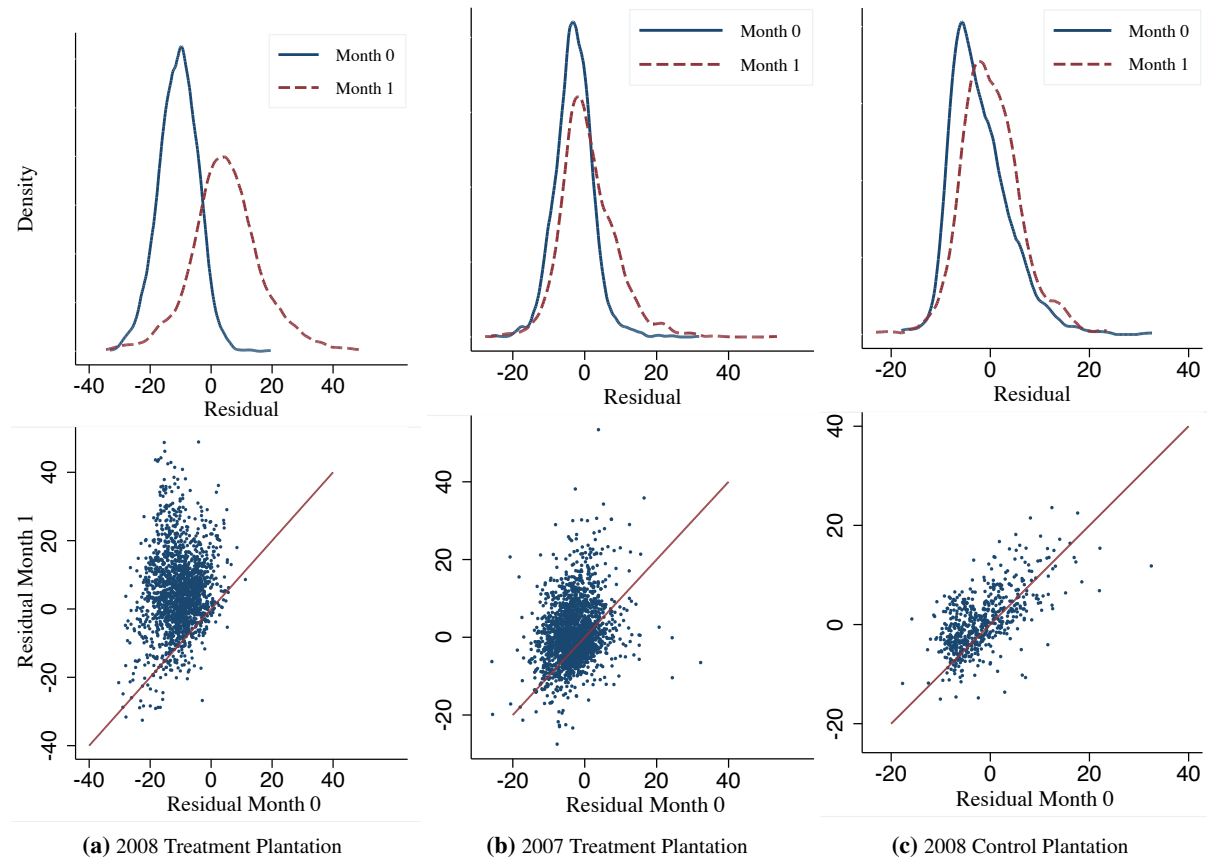


Figure O.6. Kernel Density and Scatter Plots: Average Daily Residual. *Notes.* This figure depicts kernel density estimates and worker-specific scatter plots analogous to those in Figure O.5, but using Month 0 instead of Week 0 as the baseline.

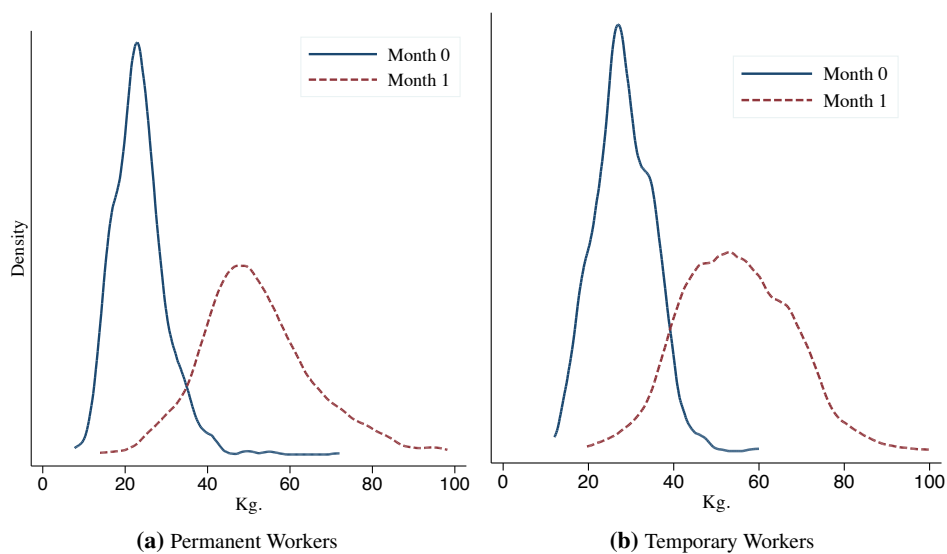


Figure O.7. Kernel Density: Average Daily Output by Permanent and Temporary Workers. *Notes.* This figure is analogous to Figure 7 in the main text, except that it uses Month 0 instead of Week 0 as the baseline.

O.4. ADDITIONAL TABLES

Dependent Variable: Output (Daily Kg. Tea)					
Month 1 over Month 0					
	First Difference			Double Difference	
	OLS (1)	OLS (2)	FE (3)	OLS (4)	OLS (5)
Counterfactual				2007 Treatment	2008 Control
After \times Treat (τ_2)				18.81*** (2.783)	22.55*** (1.798)
Treat (τ_0)				-1.31 (1.434)	-9.36*** (1.199)
After (τ_1)	24.25*** (1.935)	24.30*** (1.953)	24.36*** (0.353)	6.42*** (2.325)	1.89 (1.132)
Rainfall	0.42*** (0.061)	0.43*** (0.061)	0.41*** (0.014)	0.30*** (0.075)	0.47*** (0.086)
Shears days	-2.87 (4.267)	-2.61 (4.325)	-1.31 (1.017)	5.24* (2.869)	
Shears days ²	8.48 (5.527)	8.22 (5.621)	6.26*** (1.540)	-5.10 (3.276)	
Hand days	-19.68*** (4.962)	-19.37*** (4.966)	-18.84*** (1.553)	-10.32*** (3.657)	
Hand days ²	22.78*** (6.973)	22.35*** (6.964)	22.08*** (2.163)	15.23*** (4.295)	
Shears dummy	5.96*** (1.457)	5.92*** (1.448)	5.92*** (0.296)	8.10*** (1.075)	
Field FE	yes	yes	yes	yes	no
Worker FE	no	no	yes	no	no
Plucked at least 4 days before and after	no	yes	no	no	no
No. Observations	68,244	65,828	68,244	140,993	92,762
Adjusted R-squared	0.598	0.600	0.623	0.52	0.419
No. Unique Workers			2061		
Month 0 mean output in 2008 Treatment	25.25 (0.811)	25.26 (0.808)	25.25 (0.811)	25.25 (0.811)	25.25 (0.811)

Table O.1. Short Run Regression Estimates. *Notes.* The estimates in this table are analogous to those in Table 2 in the main text, except that this table compares Month 0 (rather than Week 0) to Month 1. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

θ	β									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.1	0.073	0.099	0.124	0.147	0.167	0.181	0.185	0.200	0.201	0.210
0.2	0.132	0.143	0.153	0.157	0.160	0.169	0.169	0.170	0.177	0.175
0.3	0.202	0.194	0.197	0.213	0.203	0.202	0.208	0.206	0.204	0.211
0.4	0.238	0.238	0.242	0.234	0.239	0.233	0.234	0.236	0.234	0.234
0.5	0.239	0.239	0.248	0.241	0.247	0.242	0.246	0.237	0.239	0.242
0.6	0.233	0.226	0.222	0.232	0.225	0.230	0.223	0.229	0.232	0.220
0.7	0.199	0.196	0.189	0.191	0.192	0.193	0.190	0.184	0.183	0.184
0.8	0.151	0.153	0.145	0.144	0.139	0.141	0.142	0.131	0.142	0.137
0.9	0.088	0.078	0.069	0.089	0.070	0.081	0.079	0.071	0.075	0.071
1.0	0.068	0.070	0.069	0.070	0.071	0.073	0.083	0.077	0.078	0.080
1.2	0.205	0.215	0.210	0.218	0.213	0.208	0.219	0.222	0.217	0.222
1.4	0.382	0.381	0.386	0.396	0.390	0.395	0.386	0.392	0.388	0.384
1.6	0.549	0.544	0.549	0.545	0.548	0.541	0.541	0.546	0.549	0.552
1.8	0.683	0.684	0.683	0.683	0.685	0.687	0.684	0.693	0.689	0.685
2.0	0.795	0.789	0.790	0.787	0.786	0.788	0.783	0.784	0.781	0.781

Table O.2. Kolmogorov-Smirnoff D Statistic: Predicted and Actual 2007 Distribution. *Notes.* This table presents Kolmogorov-Smirnoff distance statistics $D = \sup_y |F(y) - G(y)|$, which is the supremum of the absolute distances between the actual and simulated output distributions. A smaller D indicates more similar distributions. Each cell presents D for a different (θ, β) combination for which the simulation was run.

θ	β									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.1	0.552	1.030	1.469	1.894	2.299	2.591	2.880	3.239	3.406	3.689
0.2	2.363	2.619	2.775	2.930	3.059	3.077	3.223	3.323	3.345	3.420
0.3	4.629	4.684	4.721	4.740	4.854	4.721	4.855	4.789	4.725	4.847
0.4	5.666	5.641	5.668	5.664	5.552	5.601	5.456	5.530	5.476	5.427
0.5	5.436	5.330	5.296	5.279	5.284	5.141	5.253	5.079	5.156	5.180
0.6	4.582	4.459	4.322	4.422	4.367	4.312	4.176	4.275	4.219	4.058
0.7	3.199	3.245	3.157	3.063	3.090	3.092	3.059	2.990	3.006	3.013
0.8	1.877	1.908	1.849	1.767	1.722	1.699	1.726	1.712	1.724	1.629
0.9	0.501	0.464	0.355	0.471	0.366	0.355	0.339	0.293	0.325	0.257
1.0	-0.923	-0.928	-0.960	-1.045	-1.020	-0.978	-1.103	-1.081	-1.136	-1.134
1.2	-3.668	-3.756	-3.782	-3.803	-3.793	-3.816	-3.900	-3.871	-3.909	-3.894
1.4	-6.219	-6.208	-6.200	-6.248	-6.248	-6.237	-6.232	-6.292	-6.274	-6.234
1.6	-8.794	-8.780	-8.791	-8.769	-8.766	-8.734	-8.696	-8.702	-8.641	-8.690
1.8	-11.420	-11.400	-11.412	-11.370	-11.332	-11.295	-11.274	-11.263	-11.223	-11.212
2.0	-14.289	-14.190	-14.131	-14.101	-14.051	-13.992	-13.874	-13.906	-13.895	-13.839

Table O.3. Difference in Mean Output: Predicted and Actual 2007 Distribution. *Notes.* This table contains the difference between the mean of actual output and the mean of the predicted output in 2007. Each cell presents this difference for a different (θ, β) combination for which the simulation was run. The mean of the predicted output pertains to the weighted average of output for each individual for 50 replications for each of the 4 possible contracts (hand, shears and yield classes 2 and 3).

θ	β									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.1	0.009	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.5	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.6	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.7	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.9	0.012	0.021	0.074	0.019	0.069	0.076	0.091	0.144	0.103	0.200
1.0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1.2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1.4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1.6	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1.8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2.0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table O.4. p -values of t -test for Difference in Mean Output: Predicted and Actual 2007 Distribution. *Notes.* This table records p -values corresponding to the differences in Table O.3. The null hypothesis of these t -tests is that the mean of the actual and predicted distributions are equal, against the two-sided alternative. A p -value ≥ 0.10 means that we cannot reject the null of equal means at the 10% level of significance.