Inputs, Asymmetric Information, and Incentives at the Workplace*

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March 10, 2019

Abstract

This paper studies how information asymmetries over inputs between workers and managers affect the response to incentives and selection at the workplace. We develop a principal-agent model with heterogeneity and asymmetric information over input quality and worker type, and test the model predictions using personnel data from a Peruvian egg production plant. Exploiting a sudden change in the worker salary structure, we show that heterogeneity along both margins of input quality and worker type significantly affects workers' effort choice, firm profits, and worker participation differentially after the implementation of the new incentive regime. Our study reveals how information asymmetries shape the response to incentives and selection at the workplace, with implications for the design of incentive contracts.

Keywords: asymmetric information, incentives, input heterogeneity.

JEL Codes: D22, D24, J24, J33, M11, M52, M54, O12.

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*We are thankful to Oriana Bandiera, Amit Khandelwal, Eric Verhoogen, and all seminar participants at Universidad de Los Andes. Errors remain our own.

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1 Introduction

Agricultural and factory workers in both developed and developing countries are often paid with piece rates (Guiteras and Jack 2018). A large theoretical and empirical literature suggests that piece rate outperforms fixed compensation in terms of both productivity and profits (e.g., Lazear 2000). Yet, the adoption of piece rate pay varies widely across industries and over time (Helper, Kleiner, and Wang 2010; Hart and Roberts 2014). One possible explanation for this variation is the changing nature of the production technology and the structure of information at the workplace. Information over the production function and its inputs and the extent to which this is shared between workers and managers affect the design of incentive pay schemes and their effectiveness in raising productivity and profits.

In this paper, we study how the presence of asymmetric information over inputs between workers and managers affects the response to incentives and selection at the workplace. In many workplaces, and differently from the canonical model of employment relationship, workers produce output combining their effort with inputs of heterogeneous quality (Amodio and Martinez-Carrasco 2018). The quality of inputs affects the productivity of effort. In addition, workers differ in the marginal cost of effort or type. Workers are also typically better informed than managers along both dimensions, limiting the set of implementable contracts (Atkin, Chaudhry, Chaudry, Khandelwal, and Verhoogen 2017). What consequences does this have for piece rate incentive design? How does asymmetric information over input quality and worker type affect the response to incentives and worker selection at the workplace?

Providing an empirical answer to these questions is challenging for several reasons. First, data on individual production levels are not always maintained by firms, and usually not made available to researchers. Second, this is even more the case for information on inputs that are assigned to individual workers, whose quality is often not observed by the management. Third, in order to exploit meaningful variation in input quality and derive credible estimates of workers' permanent productivities, the data need to cover a sufficiently long time period. Finally, and most importantly, analyzing response to incentives requires variation in the salary structure or incentive scheme implemented at the workplace.

We overcome these limitations using the data made available by an egg production plant in rural Peru. Workers are assigned batches of hens of heterogeneous quality, exert effort to feed them, and collect eggs as output. In the first part of our sampling period, workers are paid a piece rate that increases with both the amount of food they distribute and the boxes of eggs they collect. At a given point in time, the firm shifts to a bonus scheme that only rewards workers based on output. We exploit this change in incentives combined with information on inputs and output to identify the heterogeneous response to incentives along both margins of input quality and worker type.

To guide the empirical analysis, we first develop a simple principal-agent model that incorporates all the relevant features specified above and maps into the setting of our analysis. Heterogeneous workers use inputs of heterogeneous quality and exert effort to produce noisy output. Effort and output are observable to the management, but both input quality and worker type are not, as they are only known to the worker. The asymmetry of information over input quality prevents the management from writing a contract that specifies the level of effort that the worker should exert, as that changes with unobserved input quality. In addition, workers are risk-averse, and cannot bear the risk associated with the full volatility of production. As a result, the management implements a linear contract that rewards workers for both output and effort. We characterize the optimal worker's effort choice and how it changes with the weight attached to both performance measures. The main model prediction is that, if input quality changes the sensitivity of output to effort, an increase in the weight attached to output will change worker's effort differentially according to the quality of inputs they handle. Workers of different type will also respond to the change in a differential way, with implications for worker absenteeism and retention.

We exploit the change in the piece rate bonus formula implemented by the firm, and find evidence that is consistent with the model predictions. We measure input quality using information on the expected productivity of hens as provided by a third bird supplier company, and derive a measure of worker's permanent productivity or type using data from the period prior to the incentive change. We find that, first, when incentives on output increase and those on food distributed decrease, workers reduce their feeding effort. The fall is significantly larger for workers handling inputs of higher quality, and for those with a lower marginal cost of effort. This is consistent with the evidence showing that output becomes less sensitive to feeding effort as input quality increases.

Second, we investigate the heterogeneous effects of changing incentives on output, firm profits, and worker selection or workforce composition. Output does not change differentially according to the quality of inputs or worker type. At the same time, wages decrease and output quality increases differentially for workers having a lower marginal cost of effort. These workers also distribute less food, a costly input for the firm. It follows that profits increase differentially from workers with higher permanent productivity. Consistent with the model, evidence also shows that workers with a lower marginal cost of effort are differentially and significantly more likely to skip a day of work without consent and to quit the job after the change is implemented. These results altogether indicate that unobserved input and worker heterogeneity matters in shaping worker's effort response to incentives and their effectiveness in raising firm profits, and that employment contracts have implications for worker absenteeism and retention (Lazear 2000). In the long run, the most productive workers leave the firm as a consequence of the incentive scheme change.

Our paper builds upon and contributes to several strands of the literature. A large theoretical literature exists on the trade-offs involved in performance pay, and the use of multiple performance measures (e.g., Hölmstrom 1979; Holmstrom and Milgrom 1987; Baker 1992). Starting with the seminal work of Lazear (2000), a number of empirical studies have provided convincing evidence that performance pay increases output (Prendergast 1999). The most recent empirical literature has devoted increasing attention to working arrangements in developing countries, partly because of the higher prevalence of piece rate pay. Among the others, Guiteras and Jack (2018) implement a field experiment in rural Malawi and find evidence of a positive relationship between output quantity and the piece rate. Existing studies show that response to workplace incentives changes with the degree of social connectedness (Bandiera, Barankay, and Rasul 2010), ethnic diversity (Hjort 2014), and worker's self-control (Kaur, Kremer, and Mullainathan 2015).

Our study shows that the presence of asymmetric information within organizations along the specific margins of input quality and worker type shapes the response to monetary incentives. It highlights how heterogeneity across tasks, a common features of working environments in many settings, can affect worker's performance (Adhvaryu, Kala, and Nyshadham 2016; Amodio and Martinez-Carrasco 2018). Information asymmetries between workers and managers over such heterogeneity have implications for the effectiveness of performance pay in raising productivity and profits. In this respect, our paper is related to Atkin, Chaudhry, Chaudry, Khandelwal, and Verhoogen (2017), who show how information asymmetries within the firm can slow down or prevent the adoption of productivity-enhancing technologies. More generally, our paper contributes to a growing literature that studies the role of human resource management in explaining productivity differences across firms and countries (Bloom and Van Reenen 2007; Bloom, Mahajan, McKenzie, and Roberts 2010; Bloom and Van Reenen 2010; Bloom, Eifert, Mahajan, McKenzie, and Roberts 2013).

The remainder of the paper is organized as follows. Section 2 illustrates the theoretical model that guides the empirical analysis. Section 3 provides the details of the setting under investigation, while Section 4 describe the data we use. We carry out the empirical analysis and provide the results in Section 5. Section 6 concludes.

2 Conceptual Framework

This section illustrates how asymmetric information and heterogeneity in input quality and worker type shape the worker's response to monetary incentives.[1] Let each worker i independently produce output $y_i \geq 0$ by combining her effort $a_i \geq 0$ with an input of heterogeneous

[1]In Appendix A.3, we extend the model and obtain the same predictions in a multitasking setting that allows for a second unobservable effort choice.

quality $s_i \geq 0$. Output at a given moment in time is equal to

$$y_i = f(a_i, s_i) + \varepsilon_i \tag{1}$$

where $\partial^2 f(\cdot)/\partial a_i^2 < 0$. Output is a concave function of worker's effort. We do not make any assumption on the complementarity or substitutability between a_i and s_i in production. The term ε_i captures any unobserved residual determinants of output, identically and independently distributed across workers following a normal distribution with mean zero and variance σ^2.

The cost of effort is linear and equal to $C(a_i) = \theta_i a_i$, with $\theta_i > 0$. The marginal cost of effort θ_i defines worker's type. θ_i is heterogeneous across workers, independently drawn from the same distribution. Each worker knows his type, perfectly observes input quality, and exerts effort. The management observes both effort a_i and output y_i, but has no information on input quality s_i and worker's type θ_i. Despite effort a_i being observable, the principal cannot write a contract that specifies the optimal level of effort as that depends on unobservable input quality s_i. The asymmetry of information between the worker and the management over s_i together with the presence of the idiosyncratic shock ε_i generates moral hazard and the scope for incentives.

Let the wage be equal to w_i. The worker is risk averse and has a CARA utility function $u_i = -e^{-\eta(w_i - \theta_i a_i)}$, where η is the coefficient of absolute risk aversion. Consider a contract that rewards the worker with a fixed salary plus a variable amount that depends linearly on both effort a_i and output y_i. Rewarding the worker in both dimensions can be optimal because the two metrics are informative of the worker's choice, but vary in the amount of risk they impose on the employee, and enter the principal's payoff in different ways (Hölmstrom 1979; Baker 1992).[2] In Appendix A.2, we match our empirical application by specifying the production function, and derive sufficient conditions such that the principal finds optimal to incentivize the worker on both effort a_i and output y_i.

The wage is equal to

$$w_i = f + \alpha y_i + (1 - \alpha) a_i \tag{2}$$

where f is the fixed wage component, and α is the relative weight attached to each performance measure. If $\alpha = 0$, the worker is incentivized on effort only. If $\alpha = 1$, the worker is incentivized on output only. If $0 \leq \alpha \leq 1$, the worker is incentivized on both measures. The worker chooses the effort level a_i that maximizes his utility, which is equivalent to the one maximizing the certainty equivalent

$$\hat{u}_i = f + \alpha y_i + (1 - \alpha) a_i - \theta_i a_i - \frac{\eta}{2} \alpha^2 \sigma^2 \tag{3}$$

[2]A number of theoretical papers, from Holmstrom and Milgrom (1987) to Carroll (2015), show that linear contracts can be fully optimal contracts under specific conditions.

Taking the corresponding first order condition we get

$$\frac{\partial f(s_i, a_i)}{\partial a_i} = 1 - \frac{1-\theta_i}{\alpha} \tag{4}$$

Let $1 > \theta_i \geq 1 - \alpha$. Equation 4 implicitly defines the optimal effort level a_i^* exerted by the worker. Since $\partial^2 f(\cdot)/\partial a_i^2 < 0$, it follows that

(i) $\partial a_i^*/\partial \alpha < 0$: an increase in the weight α attached to output relative to effort in measuring worker's performance decreases worker's effort;

(ii) $\partial a_i^*/\partial \theta_i < 0$: workers with higher marginal cost of effort θ_i exert less effort.

At the same time, worker's response to incentives depends on the interaction of input quality s_i and the level of effort a_i. In particular

(iii) If $\partial^3 f(s_i, a_i)/\partial a_i^2 s_i \geq 0$ then $\partial^2 a_i^*/\partial \alpha \partial s_i \leq 0$: an increase in α will decrease a_i^* relatively more for workers handling inputs of higher quality s_i;

(iv) If $\partial^3 f(s_i, a_i)/\partial a_i^2 s_i \leq 0$ then $\partial^2 a_i^*/\partial \alpha \partial s_i \geq 0$: an increase in α will decrease a_i^* relatively less for workers handling inputs of higher quality s_i.

The production function is concave with respect to effort. If the quality of inputs affects such concavity, it will also affect worker's response to incentives. This is because input quality changes the sensitivity of output to effort. If $\partial^3 f(s_i, a_i)/\partial a_i^2 s_i \geq 0$, output is less sensitive to effort at higher levels of input quality. When the salary weight attached to output increases, the optimal effort level falls disproportionally more for workers handling inputs of higher quality. The opposite holds if $\partial^3 f(s_i, a_i)/\partial a_i^2 s_i \leq 0$.

Heterogeneity in worker type also affects the response to incentives as

(v) $\partial^2 a_i^*/\partial \alpha \partial \theta_i > 0$: an increase in α decreases effort relatively less for workers with higher marginal cost θ_i.

The impact of changes to the incentive scheme on output is ambiguous. Notice that the level of effort that maximizes output is defined implicitly by setting the right-hand side of equation 4 equal to zero. The level of α that maximizes output is equal to $\tilde{\alpha} = 1 - \theta_i$. It follows that if $\alpha < \tilde{\alpha}$ worker's effort is higher than the one that would maximize output. Increasing α would decrease the level of effort and increase output. The opposite holds if $\alpha > \tilde{\alpha}$.

Participation The value of α also affects the participation constraint, with implications for worker absenteeism and retention. Starting from the expression of the worker's certainty equivalent in equation 3, we can take its derivative with respect to α and get

$$\frac{\partial \hat{u}}{\partial \alpha} = y_i - a_i + \alpha \frac{\partial y_i}{\partial \alpha} + (1 - \alpha - \theta_i) \frac{\partial a_i}{\partial \alpha} - \eta \alpha \sigma^2 \tag{5}$$

Since $\frac{\partial y_i}{\partial \alpha} = \frac{\partial f(s_i, a_i)}{\partial a_i} \frac{\partial a_i}{\partial \alpha}$ and the worker chooses the optimal effort a_i^*, we can replace the first order condition in equation 4 and obtain

$$\frac{\partial \hat{u}}{\partial \alpha} = y_i - a_i^* - \eta \alpha \sigma^2 \tag{6}$$

Taking the derivative with respect to θ_i, and given $\frac{\partial y_i}{\partial \theta_i} = \frac{\partial f(s_i, a_i)}{\partial a_i} \frac{\partial a_i}{\partial \theta_i}$, we can replace again the first order condition to get

(vi) $\partial^2 \hat{u} / \partial \alpha \partial \theta_i = -\frac{1-\theta_i}{\alpha} \frac{\partial a_i}{\partial \theta_i} > 0$: an increase in α increases expected utility on the job relatively more for workers with higher marginal cost θ_i.

Finally, utility on the job also depends on the assigned input quality:

(vii) If $\partial^3 f(s_i, a_i) / \partial a_i^2 s_i \geq 0$ then $\partial^2 a_i / \partial \theta_i \partial s_i \leq 0$ and $\partial^3 \hat{u} / \partial \alpha \partial \theta_i \partial s_i = -\frac{1-\theta_i}{\alpha} \frac{\partial^2 a_i}{\partial \theta_i \partial s_i} \geq 0$: as α increases, the expected utility on the job raises differentially more for workers with higher marginal cost θ_i who handle inputs of higher quality s_i.

3 The Setting

To test these theoretical predictions, we use personnel data from a Peruvian egg production plant (Amodio and Martinez-Carrasco 2018). This plant belongs to a company whose core business is egg production and sale. The company accounts for 22% of the national egg production in this period. The plant is organized in different *sectors*, each one with its own management, supervisors, and workers. Each sector comprises different *sheds*, long-building facilities containing one to four different *production units*.

Each worker is assigned to a production unit endowed with a batch of laying hens. All hens within a given batch share very similar characteristics. The batch as a whole is treated as a single input, as all hens within the batch are bought all together from a supplier company, raised in a dedicated sector, and moved to production accordingly. When that happens, they are assigned to a given production unit and assigned to the same worker for their entire productive life. Workers exert effort along three main dimensions: egg collection and storage, hen feeding, and cleaning and maintenance of the unit facilities. Appendix A.6 shows the typical daily schedule of a worker.

Output is measured by the number of eggs collected during the day. Mapping from our conceptual framework, this is a function of both hen characteristics or input quality and worker's effort. Hen feeding is observable by the management, which records information on the number of sacks of food distributed by the worker during the day. Effort is costly, as workers need to carry multiple 50kg sacks of food a day, walking within the production unit along cages and distributing it among all hens. Importantly, the amount of food distributed is decided by the worker and varies according to input quality. Each morning, a truck arrives at the production unit and unloads a large (unbinding) number of sacks. The worker decides how many of those to distribute during the day.[3]

Changing Incentives Workers in the firm are paid every two weeks. Their salary is equal to a fixed wage plus a bonus component that depends on worker performance as measured in a randomly chosen day within the two-week pay period. Importantly, the formula to calculate the bonus has changed over time. In the first part of our sampling period, the bonus payment is calculated according to the sum of the number of sacks of food distributed by the worker and the total number of boxes of eggs collected. If this quantity exceeds a given threshold, a piece rate is awarded for each unit above the threshold. On 24 February 2012, the company adopted a new bonus formula. This is now based on the number of boxes of eggs collected only, with no weight attached to the amount of food distributed by the worker. Such quantity is multiplied by two, and a piece rate is awarded for each unit above a given threshold, with the latter being the same across the two periods and contracts.

Mapping from our conceptual framework, the total number of boxes of eggs collected is a measure of output y_i, while the number of sacks of food distributed is a measure of worker's effort a_i. The first contract is such that $\alpha = 1/2$, and the second contract is such that $\alpha = 1$. This is the source of variation that we exploit to test the model predictions. In Appendix A.4, we show theoretically that the presence of a threshold for piece rate pay does not confound our interpretation of results as it would yield empirical predictions of opposite sign.

When asked about the reason for changing incentives, the management at the firm refers to the workers distributing "too much food" under the earlier incentive scheme. This speaks to the inability of the management to correctly specify the contract that maximizes the payoff of the firm. This is hardly surprising in the context of a large firm operating in a developing country setting (Bloom, Eifert, Mahajan, McKenzie, and Roberts 2013). Nonetheless, as we show in our empirical analysis, the implementation of the new salary scheme manages to reduce the amount of food distributed by the workers, in line with the management's expectations and goal.

[3] Production units are independent from each other and there is no scope for technological spillovers. Egg storage and manipulation is also independent across units, as each one of them is endowed with an independent warehouse for egg and food storage.

Notice that, in our conceptual framework, we do not consider the additional incentive effect of dismissal threat. In Amodio and Martinez-Carrasco (2018), we regard and model it as a salient feature of this environment, which generates free riding and negative productivity spillovers among workers. We there use only data belonging to the period after the implementation of the new bonus formula. The dismissal policy implemented at the firm does not change throughout the entire period for which we have now data and that we consider in this paper. We can therefore abstract from this issue in both our theoretical and empirical analysis.

4 Data and Descriptives

For the purpose of this study, we gained access to daily records for all production units in one sector from June 2011 to December 2012. These data cover the period from 8 months prior to 10 months following the change in the incentive scheme. We observe 94 production units in total. Across all of them, we identify 211 different hen batches. We also count 127 workers at work in the sector for at least one day.

Table A.1 in Appendix A.1 shows the summary statistics for the main variables that we use in the empirical analysis. Workers distribute 23.4 sacks of food a day on average. This quantity varies both across and within workers, with a minimum of 0.5 and a maximum of 39. As captured by the model, at least part of this variation is attributable to heterogeneity in input quality. Indeed, the productivity of hens in production varies across units over time. This is partially informed by the innate characteristics of the hens, which also determine how their productivity evolves with age. When purchased, each batch comes with detailed information on the average number of eggs per week each hen is expected to produce at every week of its age. This measure is elaborated by the seller, and is therefore exogenous to anything specific of the plant or the worker who ends up being assigned to that batch. These data are stored by the veterinary unit and are not shared with the human resource department. To get a daily measure of input quality, we divide such expected weekly productivity measure by 7. As shown in Table A.1, the measure we obtain varies from 0.02 to 0.93, with an average of 0.81.

The total number of hens per batch is also heterogenous across production units over time. This is because batches can have a different size to begin with, but also because hens may die as time goes by. Importantly, when hens within a batch die they are not replaced with new ones: only the whole batch is replaced altogether once the remaining hens reach the end of their productive life. As a result, while we observe around 10,000 hens on average per production unit, their number varies considerably from 343 to more than 15,000. Dividing the total amount of food distributed by the number of hens, we derive the amount of food per hen that is distributed by the worker, averaging 116 grams per day.

Output is given by the number of eggs collected. Workers collect an average more than 8,000 eggs per day. This corresponds to 0.8 daily eggs per hen on average, ranging from 0 to 1. Notice that the average matches the expected productivity or input quality measure closely. The data also provide information on the number of good, dirty, porous, and broken eggs – workers can turn a dirty egg into a good egg by cleaning it. We divide the number of eggs in each category by the total in order to derive measures of output quality. On average, 86% of the total number of eggs collected are good, which means they can directly move to the packaging stage. The remaining 14% is split between the other categories.

Production units are grouped in different sheds. We count 41 of them in our sample. Using information on the location of each production unit within each shed, we can calculate for each production unit the average amount of food and the average number of eggs per hen collected in neighboring production units on the same day. Finally, we complement all this information with a survey that we administered to all workers in March 2013. We are able to merge this information with those for workers that were still present on the day of the survey, which amounts to slightly more than 70% of our study sample. We use this survey to elicit information on the schooling and experience of workers, defining two dummies for whether the worker is above the mean in each dimension.

5 Empirical Analysis

Our model unambiguously predicts that the effort falls when the weight attached to output in the bonus formula increases. In this setting, the amount of food measures worker's effort. On 29 November 2011, the firm announced that it would implement a new salary structure, changing the weight α attached to output from $1/2$ to 1. The change was implemented on 24 February 2012.

Figure 1 shows the average amount of food distributed daily over time during our sampling period. The graph shows the smoothed average together with its 95% confidence interval. The two vertical red lines correspond to the dates of announcement and implementation of the new salary scheme. The amount of food distributed is stable before the announcement, falls discontinuously on announcement and implementation dates, and then seems to stabilize again in the later period at a level that is lower than the initial one. Such fall is consistent with our model prediction. But, if all workers were fully informed about the shape of the production function, we would observe effort levels to fall only on the implementation date, and stabilize immediately at the new optimum. This pattern suggests instead that workers do not hold perfect information over the shape of the production function. The announcement of a new salary structure that puts zero weight on the amount of food distributed leads the workers to decrease the amount of effort they exert along this margin. That triggers a learning process over the exact shape of the production function around the new optimum, which could explain the fall and rise in the average effort level, and its later stabilization. In another paper still work in progress, we describe and provide evidence of this learning process.

The model also predicts that, if the concavity of output with respect to effort changes with input quality, the response to a change in α will be differential along this dimension. Figure 2 plots the average number of eggs per hen collected by the worker against the amount of food per hen distributed on the same day. It does so separately for production units endowed with batches with input quality higher and lower than the median, where input quality is measured as expected productivity according to the information provided by the batch supplier. The graph plots the smoothed average together with its 95% confidence interval. Notice first that the productivity of high quality hens is always higher than the one of low quality hens. This is true at any given level of food intake. Second, the concavity of output with respect to effort is higher when input quality is lower. This means that output is less sensitive to changes in food intake when input quality is higher, i.e. $\partial^3 f(s_i, a_i)/\partial a_i^2 s_i > 0$.

5.1 Input Quality

The model predicts that, if higher input quality makes output less sensitive to effort, an increase in the weight attached to output in the bonus formula will decrease effort differentially more for those workers handling inputs of higher quality. We can test this hypothesis by exploiting the change implemented at the firm.

Figure 3 plots the average food distributed by the worker handling inputs of different quality. Specifically, it plots the average of the residuals obtained from a regression of the total number of sacks of food distributed over worker the total number of hens and worker fixed effects. We measure input quality using the information on expected productivity provided by the batch supplier. The graph shows the smoothed average together with its 95% confidence interval, separately for observations belonging to the period before and after the implementation of the new incentive scheme. First, consistent with Figure 1, evidence shows that the average amount of food distributed is lower after the change in the bonus formula. This is true for any given level of input quality. Second, Figure 3 shows that the difference between the two periods is larger when input quality is higher, which is what the model predicts.

We investigate this pattern more systematically by implementing the following difference-in-differences baseline regression specification

$$a_{igt} = \alpha + \beta \, post_t + \gamma \, s_{igt} + \delta \, s_{igt} \times post_t + \epsilon_{igt} \quad (7)$$

where a_{igt} is the total amount of food distributed by worker i operating a production unit in shed g on day t, the variable $post_t$ is a dummy equal to one for all observations belonging to the period following the implementation of the new incentive scheme, and s_{igt} is a dummy equal to one if input quality is higher than the median. To net out differences in input quantity, we include the total number of hens as a control in all specifications. The term ϵ_{igt} captures any residual determinant of the worker's choice. We allow those to be correlated both in time and space by clustering standard errors along the two dimensions of shed and day.

Our coefficient of interest is δ, which captures whether the response to the change in the bonus formula is differential according to input quality. Since $\partial^3 f(s_i, a_i)/\partial a_i^2 s_i > 0$, we expect $\delta < 0$. Identification requires that, in the absence of a change in the bonus formula, the amount of food distributed would have not changed differentially across workers handling inputs of different quality. Our measure of input quality is obtained from the batch supplier company, and is therefore exogenous to anything specific of the production process, including the workers who are ultimately assigned the input. We later show how variation in input quality does not overlap and is therefore not confounded by variation in worker types. Given that no change in technology or batch assignment rule occurred in the same period, there are no reasons to doubt the validity of the identifying assumption.

Table 1 reports the corresponding coefficient estimates. Consistent with Figure 1, the negative and significant coefficient of the $post_t$ dummy indicates that the amount food distributed falls after the implementation of the new salary scheme. As expected, the coefficient of the interaction variable is negative and highly significant: as the new contract puts a higher weight on output in the bonus formula, effort decreases differentially more for those workers handling inputs of higher quality. The coefficient remains negative, significant at the 1% level, and stable in magnitude as we progressively include worker, day, and shed fixed effects in columns 2 to 4. In column 5, we also include the interaction between input quality and a dummy equal to one for those observations belonging to the period between the announcement and the implementation of the new bonus formula. Although both coefficients of the interaction variables are negative, only the one corresponding to the period after implementation is significantly different from zero at the 1% level. Overall, these results provide evidence of a systematically differential response to incentive change along the margin of input quality in the direction that the model predicts.

5.2 Worker Type

The model also predicts that an increase in the weight attached to output in the bonus formula will decrease effort differentially less for workers with higher marginal cost of effort or worker type θ_i. To test this hypothesis, we first obtain a proxy for worker type as follows. Workers with a higher marginal cost of effort distribute less food. We thus restrict the sample to those observations belonging to the period before the announcement of the new salary scheme, and regress the number of sacks of food distributed over the proxy for input quality, the total number of hens, day, batch, and worker fixed effects. Figure 4 shows the distribution of the estimated fixed effects $\hat{\phi}_i$ that we obtain from this exercise. We regard a higher $\hat{\phi}_i$ as being associated with a lower marginal cost of effort θ_i.

We then implement the following regression specification

$$a_{igt} = \hat{\phi}_i + \beta\, post_t + \gamma\, s_{igt} + \delta\, \hat{\phi}_i \times post_t + \mu_{igt} \tag{8}$$

where $\hat{\phi}_i$ is the variable capturing the estimated worker fixed effects obtained as explained above, and the rest of the regressors are specified as in equation 7. Also in this case, the term μ_{igt} captures any residual variation in the amount of food distributed, that we allow to be correlated within shed and day. According to the model, we should expect $\delta < 0$ as workers with higher $\hat{\phi}_i$ (lower θ_i) should decrease their amount of effort differentially more after the implementation of the new bonus formula. Identification requires once again that, in the absence of a change in the bonus formula, the amount of food distributed would have not changed differentially across workers who are heterogeneous in their marginal cost of effort as proxied by $\hat{\phi}_i$.

Table 2 shows the corresponding coefficient estimates. Also in this case, the evidence is consistent with the model prediction. The estimated δ is negative and significant at the 1% level. Starting with column 3, we adopt a more flexible specification that also controls for worker fixed effects, with little change in coefficient estimates. To conclude, we combine the regression specifications in equation 7 and 8, and include all variables and interactions together. Table 3 reports the corresponding estimates.[4] The coefficients of the interaction variables are very similar to those obtained separately and reported in Table 1 and 2. This indicates that the variability in worker types does not overlap with the one in input quality. We interpret these results altogether as showing that heterogeneity along both dimensions of input quality and worker type shapes workers' response to incentives, and it does so in the way predicted by the model we presented in Section 2.

5.3 Output, Wages, and Profits

The model delivers ambiguous predictions on the effect of a change in the weight attached to output in the bonus formula on output itself. We empirically estimate this effect by implementing the same specification that we used to produce Table 3, but replacing total output measured by the total amount of egg boxes collected as dependent variable. Each box contains 360 eggs.

[4] Table A.2 in Appendix A.1 shows that results are unchanged when we use the continuous measure of input quality s_{igt} rather than a dummy for whether input quality is above the sample median.

Table 4 shows the corresponding results. Not surprisingly, higher input quality is associated with higher output. Yet, we do not find any other systematic pattern. While the estimated coefficient for $post_t$ in column 1 suggests that output fell significantly when the new bonus formula was implemented, this result is not robust to the inclusion of the full set of worker fixed effects. We also find no evidence of a differential effect on output according to the same dimensions of heterogeneity we explored in the previous analysis: input quality and worker type.[5]

Evidence shows that the new scheme achieved to reduce the amount of food that workers distribute on each day, with no discernible negative and significant effect on output. Food is costly for the firm, but the overall effect of the incentive change on profits will also depend on whether the firm pays higher or lower bonuses after its implementation. To get at that, we derive a proxy $bonus_{igt}$ for the bonus paid to worker i operating a production unit in shed g on day t. We do so by exploiting the available information on eggs collected, sacks of food distributed, and the bonus formula before and after the incentive change. Before the change, the bonus payment is calculated as a piece rate that is proportional to the sum of the number of sacks of food distributed by the worker and the total number of boxes of eggs collected. After the change, the bonus is a piece rate that increases with twice the number of boxes of eggs collected only.

We therefore obtain $bonus_{igt}$ as follows. Knowing that each box contains 360 eggs, for the period before the change we calculate

$$bonus_{igt} = \frac{1}{2}\left(\frac{y_{igt}}{360} + a_{igt}\right) \tag{9}$$

where y_{igt} is the total number of eggs collected by the worker, and a_{igt} is the amount of sacks of food distributed. For the period after the change, we calculate

$$bonus_{igt} = \frac{y_{igt}}{360} \tag{10}$$

We then implement the same regression specification that we used to produce the results in Table 3 and Table 4, replacing $bonus_{igt}$ as dependent variable. Remember that both the piece-rate parameter and the threshold for incentive pay do not change before and after the change in the bonus formula. Incorporating those would only change the scale and mean of the $bonus_{igt}$ variable, with no impact on the sign and significance of coefficient estimates.

Table 5 shows the corresponding results. In the first four columns, the coefficients of the interaction of the dummy for high input quality and the post-implementation dummy are positive and significantly different from zero. In contrast, the coefficients of the interaction with

[5] Table A.3 provides some evidence of a significant differential reduction in output along the margin of input quality in the period between the announcement and the implementation of the new payment scheme. Yet, as shown already in column 5 of Table 4, the corresponding estimate is no longer statistically significant at the standard levels when including the full set of worker, day, and shed fixed effects as controls.

the estimated worker fixed effects are negative, but insignificant at standard levels across all specifications. As in the previous tables, in column 5 we include as additional regressor the interactions with a dummy equal to one for those observations belonging to the period between the announcement and the implementation of the new salary scheme. The differential increase in the bonus paid to the workers handling high quality inputs is no longer significant when allowing for a differential effect in the transition period. Moreover, the bonus paid to workers with a higher $\hat{\phi}_i$ (lower θ_i) is differentially and significantly lower after the implementation of the new bonus formula respect to the period pre-announcement.[6] Table 3 and 4 show that both categories of workers – those handling high quality inputs and those with high permanent productivity – distribute differentially less food, with no differential effect on output. Given that the prices of eggs, food, and other inputs are not differential across workers according to type or input quality, these results would indicate that the change in the bonus formula allowed the firm to make differentially higher profits from workers handling inputs of higher quality and from those having a lower marginal cost of effort.

The previous results do not consider the possibility that the incentive change also affects the quality of output. We test this hypothesis by replacing the corresponding output quality measures as dependent variable and estimating the coefficients from the same regression specification as above. For each quality measure, Table 6 reports the main coefficient estimates from regressions without and with day and shed fixed effects. Evidence shows that the fraction of good eggs decreases differentially and significantly for workers handling inputs of higher quality, while it increases differentially for workers with higher estimated permanent productivity. This pattern is reversed when considering the fraction of broken eggs. The coefficients of interest are instead insignificant when considering the fraction of dirty and porous eggs. Table A.5 allows for a differential effect in the period between announcement and implementation. The fraction of broken eggs still significantly increases for workers handling inputs of higher quality, but the fraction of good eggs does not change differentially. On the contrary, all measures indicates that output quality increases differentially for workers with higher permanent productivity. We interpret these results altogether as showing that output quality decreases differentially for workers handling high quality inputs. To the extent to which output quality matters for revenues, this may undermine the differentially higher profitability of the incentive change for this category of workers. In contrast, output quality increases differentially for workers having a lower marginal cost of effort. Together with the previous findings, this further supports the hypothesis that the firm makes differentially higher profits from workers with higher permanent productivity after the incentive change.

Taken altogether, evidence shows that asymmetric information and heterogeneity along the two margins of input quality and worker type matters not only in determining worker's effort

[6] Table A.4 shows that these results are unchanged when allowing for a differential effect in the period between announcement and implementation of the new contract.

response to incentives, but also the effectiveness of the latter in increasing firm profits.

5.4 Absenteeism and Retention

We have so far abstained from considering the effect of the incentive change on workforce composition. The model predicts that an increase in the weight attached to output in the bonus formula will increase expected utility on the job relatively more for workers with higher marginal cost effort θ_i. This has implication for worker absenteeism and retention. In particular, given no change in the outside option of workers, we should expect absenteeism and quits to increase differentially among workers with lower marginal cost of effort.

We test this prediction by implement a logistic hazard model and study the relative odds of the probability h_{it} that the worker i is absent on day t as defined by

$$\frac{h_{it}}{1-h_{it}} = \exp\{\kappa_t + \alpha\,\psi_i + \beta\,post_t\} \tag{11}$$

where ψ_i is a dummy equal to one if the estimated worker fixed effect $\hat{\phi}_i$ estimated above is higher than the median, and $post_t$ is a dummy equal to one for all observations belonging to the period following the implementation of the new incentive scheme. κ_t captures the baseline odds of being absent, which we allow to vary with time by including the full set of month fixed effects. In other words, we let the baseline probability of absence to vary flexibly across months.

Similarly, we study the relative odds of the probability $q_i(t)$ that worker i's employment relationship terminates after t days on the job as defined by

$$\frac{q_i(t)}{1-q_i(t)} = \exp\{\gamma_t + \alpha\,\psi_i + \beta\,post_t\} \tag{12}$$

where t measures tenure on the job and is defined as days since the worker first appears in the data. We let $\gamma_t = \delta \ln t$, and we estimate δ together with α and β in order to let the baseline hazard of termination on day t to increase or decrease monotonically with tenure depending on the value of δ.[7]

We estimated both models using maximum likelihood, and derive odds ratios before and after the change for workers with fixed effects below and above the median. Table 7 reports the estimated odds ratios and their *difference-in-differences* across different specifications. In column (1), the dependent variable is a dummy equal to one if the worker is absent, while in column (2) we consider only unjustified absenteeism. We regard the latter as more apt to capture worker's

[7]Specifically, with $\gamma_t = \delta \ln t$ we let $\frac{q_(t)}{1-q_(t)} = t^{\delta}$ and $q_(t) = \frac{t^{\delta}}{1+t^{\delta}}$.

independent decisions, as the former includes absences because of sickness, paternity leaves, etc. Column (3) reports the results on employment termination. The model predicts that absenteeism and quits increase differentially after the incentive change among workers with lower marginal cost of effort (higher ψ_i). The evidence in Table 7 supports this hypothesis as it shows that the odds of unjustified absence are differentially and significantly higher for highly productive workers after the incentive change. The same is true for the probability of employment termination. This indicates that the incentive change impacts worker absenteeism, retention, and selection as the model predicts.

Finally, we test whether these effects are differential according to input quality. Since output is less sensitive to changes in food intake when input quality is higher – $\partial^3 f(s_i, a_i)/\partial a_i^2 s_i > 0$ – the model predicts that the differential positive effect on absenteeism and negative effect on retention of highly productive workers should be larger when they handle inputs of higher quality. We thus add input quality as additional determinant of absenteeism and termination in the models of equation 11 and 12 respectively. Table 8 reports the estimated odds ratios and the *triple difference* estimate of interest. The differential positive effect of the incentive change on the absenteeism of highly productive workers is significantly larger for those handling inputs of higher quality, consistent with the model prediction. We do not find instead input quality to matter differentially for the incidence of quits. This is not surprising as input quality – and thus worker's expected utility – changes over time. It is therefore reasonable to expect that it will affect absenteeism, but not necessarily the permanent decision of quitting the job.

6 Conclusions

This paper shows that asymmetric information and heterogeneity in input quality and worker type shape the response to incentives at the workplace. Using personnel data from an egg production plant in rural Peru, we exploit the variation induced by a change in the salary bonus formula combined with information on input and workers' output to show that heterogeneity in input quality is associated with a differential change in worker's effort after the implementation of the new pay regime. Workers with lower marginal cost of effort also react differentially more to the change in incentives. Our study highlights how asymmetric information between workers and managers, and imperfect information over the production technology can affect the performance of incentive pay in eliciting workers' effort and raising firm profits.

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Tables and Figures

Table 1: Incentive Change and Input Quality

	Food Distributed				
	(1)	(2)	(3)	(4)	(5)
$post_t$	-0.9425***	-0.8829***			
	(0.1659)	(0.1879)			
s_{igt}	0.7802***	0.8047***	0.6694***	0.7159***	0.8634***
	(0.1527)	(0.1741)	(0.1565)	(0.1561)	(0.1930)
$s_{igt} \times post_t$	-0.7480***	-0.8036***	-0.7169***	-0.6054***	-0.7529***
	(0.2143)	(0.2380)	(0.1982)	(0.2028)	(0.2487)
$s_{igt} \times ann_t$					-0.5038
					(0.3980)
No. of Hens	0.0023***	0.0022***	0.0022***	0.0020***	0.0020***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Worker FE	No	Yes	Yes	Yes	Yes
Day FE	No	No	Yes	Yes	Yes
Shed FE	No	No	No	Yes	Yes
Observations	46346	46345	46345	46345	46345
R^2	0.9511	0.9549	0.9589	0.9601	0.9602

Notes. (* p-value$<$0.1; ** p-value$<$0.05; *** p-value$<$0.01) Two-way clustered standard errors, with residuals grouped along both shed and day. Dependent variable is the amount of food distributed by the worker on a given day as measured by the number of 50kg sacks distributed. s_{ibt} is a dummy equal to one if input quality is higher than the median. $post_t$ is a dummy equal to one for all observations belonging to the period following the implementation of the new incentive scheme. ann_t is a dummy equal to one for all observations belonging to the period between the announcement and the implementation of the new scheme.

Table 2: Incentive Change and Worker Types

	Food Distributed				
	(1)	(2)	(3)	(4)	(5)
$post_t$	-1.6056***	-1.5273***			
	(0.1629)	(0.2193)			
$\hat{\phi}_i$	0.0856***				
	(0.0225)				
$\hat{\phi}_i \times post_t$	-0.0736***	-0.0678**	-0.0944***	-0.1104***	-0.1474***
	(0.0227)	(0.0292)	(0.0266)	(0.0296)	(0.0328)
$\hat{\phi}_i \times ann_t$					-0.0965*
					(0.0544)
s_{igt}	0.3812***	0.3711***	0.2787**	0.3840***	0.3870***
	(0.1192)	(0.1244)	(0.1069)	(0.1090)	(0.1085)
No. of Hens	0.0023***	0.0022***	0.0022***	0.0020***	0.0020***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Worker FE	No	Yes	Yes	Yes	Yes
Day FE	No	No	Yes	Yes	Yes
Shed FE	No	No	No	Yes	Yes
Observations	46346	46345	46345	46345	46345
R^2	0.9511	0.9546	0.9588	0.9602	0.9603

Notes. (* p-value$<$0.1; ** p-value$<$0.05; *** p-value$<$0.01) Two-way clustered standard errors, with residuals grouped along both shed and day. Dependent variable is the amount of food distributed by the worker on a given day as measured by the number of 50kg sacks distributed. s_{ibt} is a dummy equal to one if input quality is higher than the median. $\hat{\phi}_i$ is a variable equal to the estimated worker fixed effects from a regression of the number of sacks of food distributed over the proxy for input quality, the total number of hens, day, batch, and worker fixed effects, estimated over the subsample belonging to the period before the announcement of the change in the bonus formula. $post_t$ is a dummy equal to one for all observations belonging to the period following the implementation of the new incentive scheme. ann_t is a dummy equal to one for all observations belonging to the period between the announcement and the implementation of the new scheme.

Table 3: Incentive Change, Input Quality and Worker Types

	Food Distributed				
	(1)	(2)	(3)	(4)	(5)
$post_t$	-1.2477***	-1.1598***			
	(0.2038)	(0.2472)			
s_{igt}	0.7712***	0.8118***	0.6742***	0.7203***	0.8715***
	(0.1480)	(0.1747)	(0.1551)	(0.1540)	(0.1797)
$\hat{\phi}_i$	0.0830***				
	(0.0226)				
$s_{igt} \times post_t$	-0.7264***	-0.8151***	-0.7273***	-0.6197***	-0.7740***
	(0.2103)	(0.2402)	(0.1997)	(0.2061)	(0.2397)
$\hat{\phi}_i \times post_t$	-0.0720***	-0.0712**	-0.0964***	-0.1124***	-0.1504***
	(0.0227)	(0.0292)	(0.0265)	(0.0299)	(0.0307)
$s_{igt} \times ann_t$					-0.4802
					(0.3804)
$\hat{\phi}_i \times ann_t$					-0.0968*
					(0.0527)
No. of Hens	0.0023***	0.0022***	0.0022***	0.0020***	0.0020***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Worker FE	No	Yes	Yes	Yes	Yes
Day FE	No	No	Yes	Yes	Yes
Shed FE	No	No	No	Yes	Yes
Observations	46346	46345	46345	46345	46345
R^2	0.9515	0.9550	0.9592	0.9604	0.9606

Notes. (* p-value<0.1; ** p-value<0.05; *** p-value<0.01) Two-way clustered standard errors, with residuals grouped along both shed and day. Dependent variable is the amount of food distributed by the worker on a given day as measured by the number of 50kg sacks distributed. s_{ibt} is a dummy equal to one if input quality is higher than the median. $\hat{\phi}_i$ is a variable equal to the estimated worker fixed effects from a regression of the number of sacks of food distributed over the proxy for input quality, the total number of hens, day, batch, and worker fixed effects, estimated over the subsample belonging to the period before the announcement of the change in the bonus formula. $post_t$ is a dummy equal to one for all observations belonging to the period following the implementation of the new incentive scheme. ann_t is a dummy equal to one for all observations belonging to the period between the announcement and the implementation of the new scheme.

Table 4: Incentive Change and Output

	Total No. of Eggs Boxes Collected				
	(1)	(2)	(3)	(4)	(5)
$post_t$	-1.3178*	-1.0176			
	(0.6576)	(0.7560)			
s_{igt}	2.8060***	3.2736***	3.1615***	3.3731***	3.9290***
	(0.3717)	(0.4559)	(0.4836)	(0.4947)	(0.6544)
$\hat{\phi}_i$	0.0104				
	(0.0537)				
$s_{igt} \times post_t$	-0.0476	-0.3539	-0.2912	-0.1405	-0.7071
	(0.6046)	(0.6560)	(0.6089)	(0.6512)	(0.7557)
$\hat{\phi}_i \times post_t$	-0.0245	0.0088	-0.0139	-0.0300	-0.0634
	(0.0678)	(0.0847)	(0.0782)	(0.0873)	(0.0805)
$s_{igt} \times ann_t$					-1.8645
					(1.1134)
$\hat{\phi}_i \times ann_t$					-0.0809
					(0.1458)
No. of Hens	0.0022***	0.0020***	0.0020***	0.0015***	0.0016***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Worker FE	No	Yes	Yes	Yes	Yes
Day FE	No	No	Yes	Yes	Yes
Shed FE	No	No	No	Yes	Yes
Observations	46346	46345	46345	46345	46345
R^2	0.7010	0.7241	0.7325	0.7380	0.7388

Notes. (* p-value$<$0.1; ** p-value$<$0.05; *** p-value$<$0.01) Two-way clustered standard errors, with residuals grouped along both shed and day. Dependent variable is total output as measured by the total amount of eggs boxes collected by the worker on a given day. Eggs boxes contain 360 eggs. s_{ibt} is a dummy equal to one if input quality is higher than the median. $\hat{\phi}_i$ is a variable equal to the estimated worker fixed effects from a regression of the number of sacks of food distributed over the proxy for input quality, the total number of hens, day, batch, and worker fixed effects, estimated over the subsample belonging to the period before the announcement of the change in the bonus formula. $post_t$ is a dummy equal to one for all observations belonging to the period following the implementation of the new incentive scheme.

Table 5: Incentive Change and Bonus Paid

	Bonus Paid (derived)				
	(1)	(2)	(3)	(4)	(5)
$post_t$	-2.4269***	-2.1914***			
	(0.4948)	(0.5905)			
s_{igt}	1.7940***	2.0408***	1.9075***	2.0491***	2.4370***
	(0.2435)	(0.3334)	(0.3441)	(0.3480)	(0.4332)
$\hat{\phi}_i$	0.0601				
	(0.0390)				
$s_{igt} \times post_t$	0.9531*	0.8689	0.9532*	1.1361**	0.7356
	(0.5040)	(0.5564)	(0.5052)	(0.5392)	(0.5904)
$\hat{\phi}_i \times post_t$	-0.0809	-0.0467	-0.0701	-0.0871	-0.1183*
	(0.0538)	(0.0659)	(0.0609)	(0.0681)	(0.0623)
$s_{igt} \times ann_t$					-1.2901*
					(0.7382)
$\hat{\phi}_i \times ann_t$					-0.0770
					(0.0976)
No. of Hens	0.0022***	0.0020***	0.0020***	0.0016***	0.0017***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Worker FE	No	Yes	Yes	Yes	Yes
Day FE	No	No	Yes	Yes	Yes
Shed FE	No	No	No	Yes	Yes
Observations	46346	46345	46345	46345	46345
R^2	0.7555	0.7740	0.7823	0.7864	0.7868

Notes. (* p-value<0.1; ** p-value<0.05; *** p-value<0.01) Two-way clustered standard errors, with residuals grouped along both shed and day. Sample is restricted to those observations belonging to the period before announcement and after implementation of the new incentive scheme. Dependent variable is a proxy for the bonus paid to workers derived using the number of eggs collected, the total amount of sacks of food distributed, and the bonus formula before and after the incentive change, as explained in Section 5.3. s_{ibt} is a dummy equal to one if input quality is higher than the median. $\hat{\phi}_i$ is a variable equal to the estimated worker fixed effects from a regression of the number of sacks of food distributed over the proxy for input quality, the total number of hens, day, batch, and worker fixed effects, estimated over the subsample belonging to the period before the announcement of the change in the bonus formula. $post_t$ is a dummy equal to one for all observations belonging to the period following the implementation of the new incentive scheme.

Table 6: Incentive Change and Output Quality

	Good/Total		Dirty/Total		Porous/Total		Broken/Total	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$post_t$	0.0244		-0.0067		-0.0099		-0.0030	
	(0.0156)		(0.0042)		(0.0111)		(0.0034)	
s_{igt}	0.0796***	0.0768***	-0.0151***	-0.0119***	-0.0549***	-0.0529***	-0.0079***	-0.0085***
	(0.0073)	(0.0085)	(0.0032)	(0.0023)	(0.0066)	(0.0069)	(0.0015)	(0.0016)
$s_{igt} \times post_t$	-0.0241*	-0.0254*	-0.0026	-0.0039	0.0120	0.0140	0.0127**	0.0128***
	(0.0138)	(0.0146)	(0.0042)	(0.0034)	(0.0102)	(0.0104)	(0.0056)	(0.0047)
$\hat{\phi}_i \times post_t$	0.0047**	0.0045**	-0.0012	-0.0013	-0.0020	-0.0018	-0.0009*	-0.0009*
	(0.0019)	(0.0019)	(0.0009)	(0.0009)	(0.0012)	(0.0011)	(0.0005)	(0.0005)
No. of hens	0.0000***	0.0000***	-0.0000***	-0.0000***	-0.0000**	-0.0000***	0.0000***	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Outcome Mean	0.858	0.858	0.060	0.060	0.052	0.052	0.020	0.020
Worker FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	No	Yes	No	Yes	No	Yes	No	Yes
Shed FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	46078	46078	46078	46078	46078	46078	46078	46078
R^2	0.2534	0.3335	0.2762	0.4213	0.3049	0.3662	0.1145	0.3195

Notes. (* p-value$<$0.1; ** p-value$<$0.05; *** p-value$<$0.01) Two-way clustered standard errors, with residuals grouped along both shed and day. Dependent variables are different measures of output quality: the number of good, dirty, porous, and broken eggs. s_{ibt} is a dummy equal to one if input quality is higher than the median. $\hat{\phi}_i$ is a variable equal to the estimated worker fixed effects from a regression of the number of sacks of food distributed over the proxy for input quality, the total number of hens, day, batch, and worker fixed effects, estimated over the subsample belonging to the period before the announcement of the change in the bonus formula. $post_t$ is a dummy equal to one for all observations belonging to the period following the implementation of the new incentive scheme.

Table 7: Worker Type, Absenteeism and Termination - Odds Ratios

	Absence (1)	Unjustified (2)	Termination (3)
Before Change High Productivity	0.0865*** (0.0048)	0.0509*** (0.0038)	0.0011*** (0.0003)
Before Change Low Productivity	0.0584*** (0.0019)	0.0331*** (0.0013)	0.0048*** (0.0006)
After Change High Productivity	0.0579*** (0.0024)	0.0367*** (0.0018)	0.0011*** (0.0003)
After Change Low Productivity	0.0409*** (0.0015)	0.0271*** (0.0012)	0.0014*** (0.0003)
Diff-in-Diff	-0.0111*** (0.0021)	0.0060*** (0.0018)	0.0034*** (0.0005)
Month FE	Yes	Yes	No
Observations	40285	40338	32708

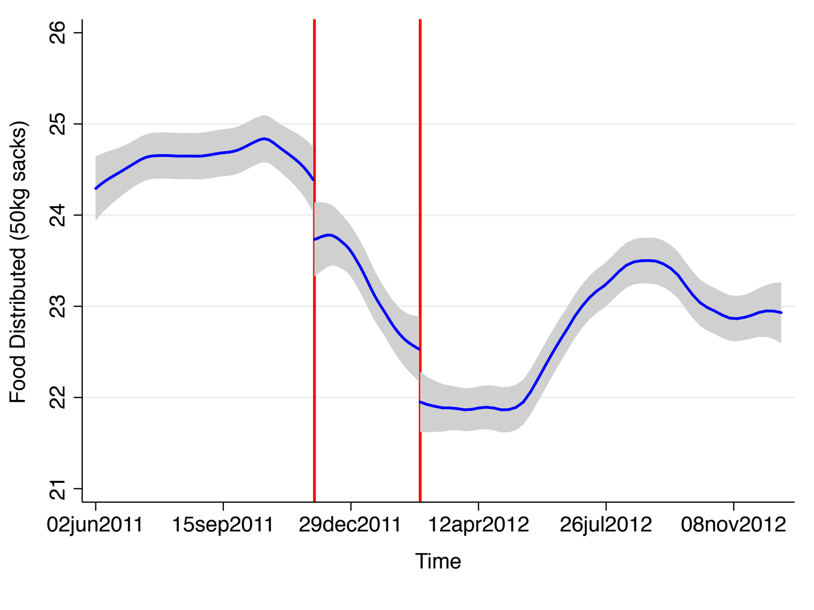
Notes. (* p-value$<$0.1; ** p-value$<$0.05; *** p-value$<$0.01) Logit estimates. In column (1), dependent variable is dummy equal to 1 if the worker is absent. In column (2), dependent variable is dummy equal to 1 if the worker is absent without justification. In column (3), dependent variable is dummy equal to 1 if the employment relationship terminates. The table reports the estimated odds ratios for workers whose estimated fixed effects are above and below the median before and after the incentive change, together with the difference in differences.

Table 8: Worker Type, Input Quality, Absenteeism and Termination - Odds Ratios

	Absence (1)	Unjustified (2)	Termination (3)
Before Change High Productivity High Input Quality	0.0259*** (0.0026)	0.0185*** (0.0021)	0.0008*** (0.0002)
Before Change Low Productivity High Input Quality	0.0238*** (0.0016)	0.0179*** (0.0014)	0.0039*** (0.0008)
After Change High Productivity High Input Quality	0.0184*** (0.0014)	0.0117*** (0.0010)	0.0009*** (0.0003)
After Change Low Productivity High Input Quality	0.0180*** (0.0012)	0.0122*** (0.0010)	0.0011*** (0.0003)
Before Change High Productivity Low Input Quality	0.0364*** (0.0037)	0.0310*** (0.0035)	0.0015*** (0.0005)
Before Change Low Productivity Low Input Quality	0.0301*** (0.0016)	0.0271*** (0.0015)	0.0053*** (0.0008)
After Change High Productivity Low Input Quality	0.0211*** (0.0016)	0.0160*** (0.0014)	0.0013*** (0.0004)
After Change Low Productivity Low Input Quality	0.0200*** (0.0013)	0.0163*** (0.0012)	0.0016*** (0.0004)
Triple-Diff	0.0036*** (0.0010)	0.0031*** (0.0011)	-0.0004 (0.0007)
Month FE	Yes	Yes	No
Observations	36542	37595	32708

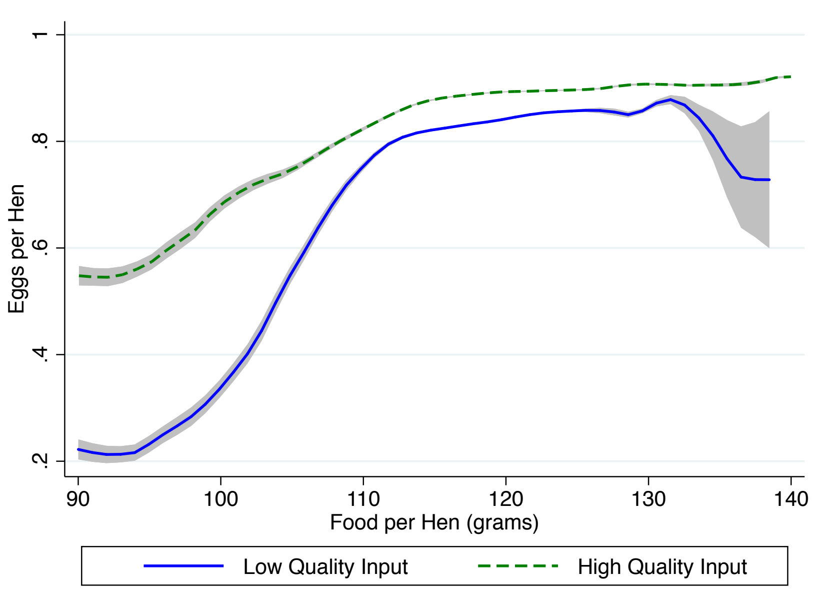
Notes. (* p-value<0.1; ** p-value<0.05; *** p-value<0.01) Logit estimates. In column (1), dependent variable is dummy equal to 1 if the worker is absent. In column (2), dependent variable is dummy equal to 1 if the worker is absent without justification. In column (3), dependent variable is dummy equal to 1 if the employment relationship terminates. The table reports the estimated odds ratios for workers whose estimated fixed effects are above and below the median before and after the incentive change, and separately for assigned input quality above and below the median, together with the corresponding triple differences.

Figure 1: Food Choice Over Time



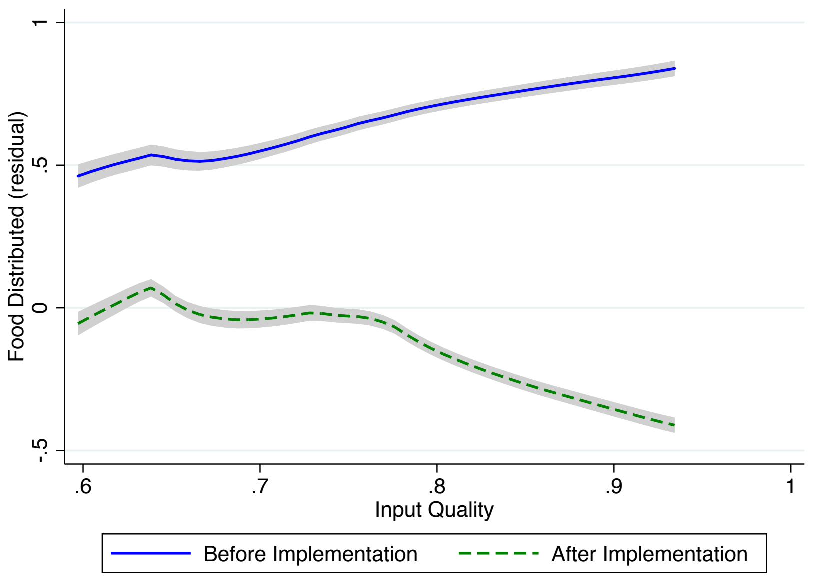
Notes. The figure plots the smoothed average of the total number of 50kgs sacks of food distributed across all production units in a given day, together with its 95% confidence interval. Residuals are obtained from a regression of the number sacks distributed over the proxy for input quality and worker fixed effects. The two vertical lines correspond to the dates of announcement and implementation of the new incentive scheme. The amount of food distributed is stable before the announcement, falls discontinuously on announcement and implementation dates, and stabilizes again in the later period at a level that is lower than the initial one.

Figure 2: Food Intake and Output



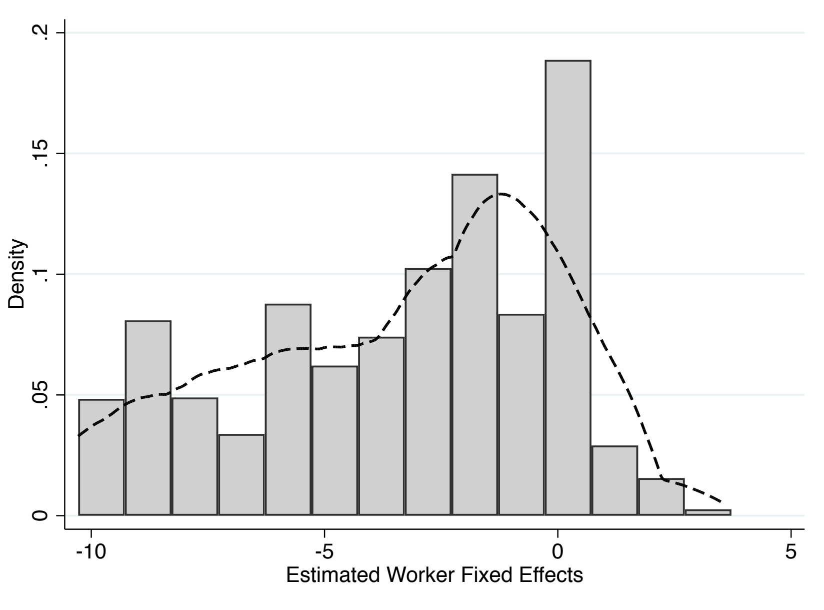
Notes. The figure plots the smoothed average of the number of eggs per hen collected by the worker over the grams of food per hen distributed in the day, together with its 95% confidence interval. It does so separately for production units endowed with batch of above and below median quality, where the latter is measured using the expected productivity measure available from the supplier company upon purchasing the batch.

Figure 3: Incentive Change and Input Quality



Notes. The figure plots the smoothed average of the number of sacks of food distributed across all production units endowed with inputs of different quality, together with its 95% confidence interval. It does so separately for observations belonging to the period before and after the incentive change. Residuals are obtained from a regression of the number sacks distributed over worker fixed effects and the total number of hens.

Figure 4: Distribution of Worker Type



Notes. The figure plots the estimated worker fixed effects from a regression of the number of sacks of food distributed over the proxy for input quality, the total number of hens, day, batch, and worker fixed effects, estimated over the subsample belonging to the period before the announcement of the change in the bonus formula.

A Appendix

A.1 Additional Tables and Figures

Table A.1: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Food Distributed (50kg sacks)	23.402	8.705	0.5	39	46049
Input Quality	0.811	0.147	0.02	0.934	44985
No. of Hens	10105.576	3672.284	353	15985	46049
Food per Hen (gr)	115.771	9.495	66.774	163.235	46049
Total Eggs Collected	8140.025	3574.481	0	15131	46049
Total Eggs per Hen	0.803	0.19	0	1	46049
Food Distributed by Coworkers (avg)	24.255	7.302	1	35.5	42281
Coworkers' Total Eggs per Hen (avg)	0.807	0.154	0	1	42281
Good/Total	0.858	0.089	0	1.766	40082
Dirty/Total	0.060	0.043	0	0.769	40082
Porous/Total	0.052	0.061	0	1	40082
Broken/Total	0.020	0.030	0	0.5	40082
Experienced	0.498	0.500	0	1	32899
High Schooling	0.534	0.499	0	1	32899

Notes. The table reports the summary statistics of the variable used in the empirical analysis.

Table A.2: Incentive Change, Input Quality and Worker Types - Continuous s_{igt}

	Food Distributed				
	(1)	(2)	(3)	(4)	(5)
$post_t$	-0.6834	-0.4924			
	(0.5550)	(0.6042)			
s_{igt}	5.5803***	5.8282***	5.5468***	5.6325***	5.9022***
	(0.4139)	(0.4548)	(0.3802)	(0.3678)	(0.3752)
$\hat{\phi}_i$	0.0963***				
	(0.0271)				
$s_{igt} \times post_t$	-1.2458*	-1.4255**	-1.1163**	-0.5778	-0.8488
	(0.6320)	(0.6569)	(0.5383)	(0.5849)	(0.6003)
$\hat{\phi}_i \times post_t$	-0.0796***	-0.0798***	-0.1050***	-0.1234***	-0.1676***
	(0.0231)	(0.0287)	(0.0258)	(0.0267)	(0.0332)
$s_{igt} \times ann_t$					-0.9620
					(1.3227)
$\hat{\phi}_i \times ann_t$					-0.1146**
					(0.0564)
No. of Hens	0.0023***	0.0022***	0.0022***	0.0019***	0.0019***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Worker FE	No	Yes	Yes	Yes	Yes
Day FE	No	No	Yes	Yes	Yes
Shed FE	No	No	No	Yes	Yes
Observations	45279	45279	45279	45279	45279
R^2	0.9568	0.9604	0.9644	0.9664	0.9666

Notes. (* p-value$<$0.1; ** p-value$<$0.05; *** p-value$<$0.01) Two-way clustered standard errors, with residuals grouped along both shed and day. Dependent variable is the amount of food distributed by the worker on a given day as measured by the number of 50kg sacks distributed. s_{ibt} is the continuous input quality measure. $\hat{\phi}_i$ is a variable equal to the estimated worker fixed effects from a regression of the number of sacks of food distributed over the proxy for input quality, the total number of hens, day, batch, and worker fixed effects, estimated over the subsample belonging to the period before the announcement of the change in the bonus formula. $post_t$ is a dummy equal to one for all observations belonging to the period following the implementation of the new incentive scheme. ann_t is a dummy equal to one for all observations belonging to the period between the announcement and the implementation of the new scheme.

Table A.3: Incentive Change and Output: Announcement and Implementation

	Total No. of Eggs Boxes Collected			
	(1)	(2)	(3)	(4)
$post_t$	-1.3990*	-1.3002		
	(0.7841)	(0.8709)		
ann_t	-0.1472	-0.4936		
	(1.3321)	(1.3369)		
s_{igt}	3.2589***	3.7349***	3.7399***	3.9290***
	(0.5315)	(0.6417)	(0.6246)	(0.6544)
$\hat{\phi}_i$	0.0343			
	(0.0678)			
$s_{igt} \times post_t$	-0.5015	-0.8070	-0.8737	-0.7071
	(0.7205)	(0.8124)	(0.6963)	(0.7557)
$\hat{\phi}_i \times post_t$	-0.0479	-0.0436	-0.0488	-0.0634
	(0.0661)	(0.0756)	(0.0769)	(0.0805)
$s_{igt} \times ann_t$	-1.8327*	-1.8170*	-1.9989*	-1.8645
	(0.9267)	(1.0418)	(1.0511)	(1.1134)
$\hat{\phi}_i \times ann_t$	-0.0548	-0.1077	-0.0923	-0.0809
	(0.1388)	(0.1430)	(0.1396)	(0.1458)
No. of Hens	0.0022***	0.0020***	0.0020***	0.0016***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Worker FE	No	Yes	Yes	Yes
Day FE	No	No	Yes	Yes
Shed FE	No	No	No	Yes
Observations	46346	46345	46345	46345
R^2	0.7024	0.7256	0.7334	0.7388

Notes. (* p-value$<$0.1; ** p-value$<$0.05; *** p-value$<$0.01) Two-way clustered standard errors, with residuals grouped along both shed and day. Dependent variable is total output as measured by the total amount of eggs boxes collected by the worker on a given day. Eggs boxes contain 360 eggs. s_{ibt} is a dummy equal to one if input quality is higher than the median. $\hat{\phi}_i$ is a variable equal to the estimated worker fixed effects from a regression of the number of sacks of food distributed over the proxy for input quality, the total number of hens, day, batch, and worker fixed effects, estimated over the subsample belonging to the period before the announcement of the change in the bonus formula. $post_t$ is a dummy equal to one for all observations belonging to the period following the implementation of the new incentive scheme.

Table A.4: Incentive Change and Bonus Paid - Announcement and Implementation

	Bonus Paid (derived)			
	(1)	(2)	(3)	(4)
$post_t$	-2.6741***	-2.6029***		
	(0.5290)	(0.6365)		
ann_t	-0.6855	-0.8720		
	(0.8441)	(0.8487)		
s_{igt}	2.0180***	2.3201***	2.3151***	2.4370***
	(0.3259)	(0.4268)	(0.4160)	(0.4332)
$\hat{\phi}_i$	0.0888*			
	(0.0484)			
$s_{igt} \times post_t$	-1.0338*	-1.2204*	-1.3955*	-1.2901*
	(0.5906)	(0.6732)	(0.6910)	(0.7382)
$\hat{\phi}_i \times post_t$	-0.0702	-0.1064	-0.0910	-0.0770
	(0.0923)	(0.0958)	(0.0932)	(0.0976)
$s_{igt} \times ann_t$	0.7260	0.5953	0.5389	0.7356
	(0.5588)	(0.6423)	(0.5443)	(0.5904)
$\hat{\phi}_i \times ann_t$	-0.1088**	-0.1001*	-0.1040*	-0.1183*
	(0.0497)	(0.0588)	(0.0595)	(0.0623)
No. of Hens	0.0022***	0.0020***	0.0020***	0.0017***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Worker FE	No	Yes	Yes	Yes
Day FE	No	No	Yes	Yes
Shed FE	No	No	No	Yes
Observations	46346	46345	46345	46345
R^2	0.7566	0.7754	0.7828	0.7868

Notes. (* p-value<0.1; ** p-value<0.05; *** p-value<0.01) Two-way clustered standard errors, with residuals grouped along both shed and day. Sample is restricted to those observations belonging to the period before announcement and after implementation of the new incentive scheme. Dependent variable is a proxy for the bonus paid to workers derived using the number of eggs collected, the total amount of sacks of food distributed, and the bonus formula before and after the incentive change, as explained in Section 5.3. s_{ibt} is a dummy equal to one if input quality is higher than the median. $\hat{\phi}_i$ is a variable equal to the estimated worker fixed effects from a regression of the number of sacks of food distributed over the proxy for input quality, the total number of hens, day, batch, and worker fixed effects, estimated over the subsample belonging to the period before the announcement of the change in the bonus formula. $post_t$ is a dummy equal to one for all observations belonging to the period following the implementation of the new incentive scheme.

Table A.5: Incentive Change and Output Quality - Announcement and Implementation

	Good/Total		Dirty/Total		Porous/Total		Broken/Total	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$post_t$	0.0255		-0.0020		-0.0132		-0.0043	
	(0.0156)		(0.0059)		(0.0110)		(0.0035)	
ann_t	0.0039		0.0105		-0.0082		-0.0036	
	(0.0204)		(0.0071)		(0.0156)		(0.0028)	
s_{igt}	0.0801***	0.0770***	-0.0136***	-0.0119***	-0.0557***	-0.0527***	-0.0091***	-0.0093***
	(0.0097)	(0.0105)	(0.0042)	(0.0028)	(0.0081)	(0.0084)	(0.0019)	(0.0020)
$s_{igt} \times post_t$	-0.0245	-0.0257	-0.0043	-0.0039	0.0128	0.0138	0.0138**	0.0135***
	(0.0159)	(0.0156)	(0.0055)	(0.0039)	(0.0112)	(0.0114)	(0.0062)	(0.0050)
$\hat{\phi}_i \times post_t$	0.0055***	0.0054***	-0.0014	-0.0019*	-0.0025**	-0.0021*	-0.0011**	-0.0009**
	(0.0018)	(0.0019)	(0.0012)	(0.0010)	(0.0012)	(0.0012)	(0.0004)	(0.0004)
$s_{igt} \times ann_t$	-0.0054	-0.0016	-0.0001	0.0005	0.0022	-0.0005	0.0037	0.0026
	(0.0183)	(0.0189)	(0.0059)	(0.0048)	(0.0141)	(0.0138)	(0.0029)	(0.0031)
$\hat{\phi}_i \times ann_t$	0.0028	0.0024	-0.0013	-0.0015*	-0.0012	-0.0007	-0.0003	-0.0001
	(0.0021)	(0.0020)	(0.0010)	(0.0008)	(0.0014)	(0.0015)	(0.0003)	(0.0003)
No. of hens	0.0000***	0.0000***	-0.0000***	-0.0000***	-0.0000**	-0.0000***	0.0000***	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Outcome Mean	0.858	0.858	0.060	0.060	0.052	0.052	0.020	0.020
Worker FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	No	Yes	No	Yes	No	Yes	No	Yes
Shed FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	46078	46078	46078	46078	46078	46078	46078	46078
R^2	0.2554	0.3342	0.2883	0.4224	0.3054	0.3663	0.1150	0.3196

Notes. (* p-value<0.1; ** p-value<0.05; *** p-value<0.01) Two-way clustered standard errors, with residuals grouped along both shed and day. Dependent variables are different measures of output quality: the number of good, dirty, porous, and broken eggs. s_{ibt} is a dummy equal to one if input quality is higher than the median. $\hat{\phi}_i$ is a variable equal to the estimated worker fixed effects from a regression of the number of sacks of food distributed over the proxy for input quality, the total number of hens, day, batch, and worker fixed effects, estimated over the subsample belonging to the period before the announcement of the change in the bonus formula. $post_t$ is a dummy equal to one for all observations belonging to the period following the implementation of the new incentive scheme.

TABLE A.6: WORKER'S TYPICAL WORKING DAY

6.20am	Breakfast at the cafeteria, a truck takes them to the assigned production unit
7.00am	Hens' feeding, food distribution and even up
9.00am	Egg collection
11.30am	Egg classification (good, dirty, porous and broken) and cleaning
12.30am	Truck arrives to collect egg baskets
1.00pm	Lunch at the cafeteria
1.30pm	Eggs moved to boxes
2.30pm	Truck takes them back to production unit
3.00pm	Cleaning of cages and facilities
3.30pm	Hens' feeding, food distribution and even up
5.00pm	End of working day

A.2 Optimal Linear Contract

In this section, we derive the value of α that is optimal for the principal after assuming a shape of the production function that matches our setting. In our application, the concavity of output with respect to effort is lower when input quality increases, meaning $\partial^3 f(s_i, a_i)/\partial a_i^2 s_i > 0$. We incorporate this property parsimoniously in a production function of the form

$$y_i = \frac{1}{s_i}(a_i - a_i^2) \tag{A.1}$$

Solving for a_i in the first order condition of the worker's maximization problem in equation 4 of Section 2 yields

$$a_i^* = \frac{1}{2} - \frac{s_i}{2}\left(1 - \frac{1-\theta_i}{\alpha}\right) \tag{A.2}$$

In our setting, worker's effort a_i maps into number of sacks of food distributed. Since food is costly, this enters the principal's payoff directly together with output. We assume the principal to be risk neutral and have a linear utility that is given by

$$v_i = y_i - w_i - \gamma a_i \tag{A.3}$$

where γ is the cost of food per unit of worker's effort, and $w_i = f + \alpha y_i + (1-\alpha)a_i$. The problem of the principal is to find the values of f and α that maximize her payoff. In doing this, she takes into account the optimal choice of the worker in equation A.2 above, and her participation constraint. We assume without loss of generality that the value of the outside option for the worker is equal to zero. We thus have

$$f^* = \frac{\eta}{2}\alpha^2\sigma^2 + \theta_i a_i^* - \alpha y_i(s_i, a_i^*) - (1-\alpha)a_i^* \tag{A.4}$$

where

$$y_i(s_i, a_i^*) = \frac{1}{s_i}\left[\frac{1}{4} - \frac{s_i^2}{4}\left(1 - \frac{1-\theta_i}{\alpha}\right)^2\right] \tag{A.5}$$

The principal chooses α that maximizes

$$v_i = y_i(s_i, a_i^*) - \frac{\eta}{2}\alpha^2\sigma^2 - \theta_i a_i^* - \gamma a_i \tag{A.6}$$

It can be shown that if $\gamma = 0$ and $\sigma^2 = 0$ the optimal value of α is equal to one. This is because the principal bears no cost associated with worker's effort, and the worker is risk neutral: the contract with $\alpha = 1$ implements the first-best allocation of effort. With $\gamma > 0$ and $\sigma^2 = 0$, the optimal value of α is greater than one: the principal attaches a negative weight to worker's effort as that is associated with additional costs. However, if σ^2 is sufficiently high, the optimal α is positive but lower than one. This is because incentives on output make the worker bear risk, while, despite the negative sign in the principal's payoff, incentives on effort work as an insurance mechanism.

A.3 Model Extension: Multitasking

This section extend the previous model and informational structure to show that the same predictions hold in a multitasking setting. Assume each worker have two types of effort, a_1 and a_2, each of them related to a particular action. In our setting, we can think at those actions as being feeding hens and collecting eggs. It is worth highlight here two important features of our setting. First, feeding effort is closely captured by the amount of food distributed among hens, but the effort devoted to collecting eggs has no a clear performance measure related to it: the total amount of eggs a worker collects depends on efforts and input quality. Second, unlike some formulations of the multitasking setting, these efforts do not compete for a given amount of time of effort, since there is a predetermined schedule for the workers as shown in Table A.6. The latter is important because what matters is the intensity of the effort provided and not the amount of time spent on a given task, which implies that we can rule out corner solutions. Taking in account the previous considerations we assume a production function of the form

$$y_i = f(a_{1i}, a_{2i}, s_i) + \epsilon_i$$

As before, the cost of effort is linear, $C(a_i) = \theta_i a_i$ where $\theta_i > 0$ and $a_i = a_{1i} + a_{2i}$. The wage is equal to $w_i = f + \alpha y_i + (1 - \alpha)a_{1i}$. The manager observes perfectly feeding effort a_{1i} and uses this information in the contract to reduce the risk borne by workers as shown in Appendix A.2. Given the CARA utility function of the workers, we can solve for the first order conditions of the worker's problem:

$$\begin{aligned} \frac{\partial f}{\partial a_{1i}} &= 1 - \left(\frac{1-\theta_i}{\alpha}\right) \\ \frac{\partial f}{\partial a_{2i}} &= \frac{\theta_i}{\alpha} \end{aligned} \tag{A.7}$$

Notice that the equation determining a_{1i} is the same first order condition we obtained before in equation 4. However, the worker can adjust now both efforts as a response to the change of the relevant variables. In this section, we show that we obtain the same predictions of Section 2 in the multitasking context when the following conditions are met

1. The production function is concave is both effort types: $\frac{\partial f}{\partial a_i} > 0$ and $\frac{\partial^2 f}{\partial a_i^2} < 0$ for $i = 1, 2$;
2. Direct effects are stronger than indirect effects over the slope of the production function with respect to both effort types: $\mid \frac{\partial^2 f}{\partial a_i^2} \mid > \mid \frac{\partial^2 f}{\partial a_1 \partial a_2} \mid$ for $i = 1, 2$;
3. The sensitivity of the production function to a_2 and the complementarity among actions is not affected by input quality: $\frac{\partial^3 f}{\partial a_2^2 \partial s} = 0$ and $\frac{\partial^3 f}{\partial a_1 \partial a_2 \partial s} = 0$;
4. The sensitivity of the production function to a_1 and a_2 and the complementarity among effort types is not affected by the incentive scheme parameter α: $\frac{\partial^3 f}{\partial a_i^2 \partial \alpha} = 0$ for $i = 1, 2$ and $\frac{\partial^3 f}{\partial a_1 \partial a_2 \partial \alpha} = 0$.

The first condition ensures that marginal returns to each effort are decreasing. The second conditions implies that direct effects are more important than indirect effects when exogenous parameters change. This makes sense in our context, where workers are low skill, have well-defined schedules and it is difficult for them to capture the strategic impact of their effort movements. Finally, the third condition denotes that both the sensitivity of the production function to the amount of effort spent on collecting eggs and the degree of complementarity among effort types do not change with input quality. Yet, notice that no assumption is made regarding the degree of complementarity between the two effort types. Finally, the fourth condition ensures that the concavity of the production function with respect to both worker efforts and the degree of complementarity among them among them are not affected by the parameter defining the composite performance measure on the contract. Now, we show that the main predictions are satisfied:

From the previous first order conditions, taking derivatives respect to α we get

$$\frac{\partial^2 f}{\partial a_{1i}^2}\frac{\partial a_{1i}}{\partial \alpha} + \frac{\partial^2 f}{\partial a_{1i}\partial a_{2i}}\frac{\partial a_{2i}}{\partial \alpha} = \frac{1-\theta_i}{\alpha^2} \tag{A.8}$$

$$\frac{\partial^2 f}{\partial a_{1i}\partial a_{2i}}\frac{\partial a_{1i}}{\partial \alpha} + \frac{\partial^2 f}{\partial a_{2i}^2}\frac{\partial a_{2i}}{\partial \alpha} = -\frac{\theta_i}{\alpha^2} \tag{A.9}$$

Clearing $\partial a_{2i}/\partial\alpha$ from equation A.9 and replacing it in A.8 we get

$$\Gamma\frac{\partial a_{1i}}{\partial \alpha} = \frac{\theta_i}{\alpha^2} f_{a_{1i}a_{2i}} + \frac{1-\theta_i}{\alpha^2} f''_{a_{2i}} \tag{A.10}$$

where $\Gamma = \left[\frac{\partial^2 f}{\partial a_{1i}^2}\frac{\partial^2 f}{\partial a_{2i}^2} - \left(\frac{\partial^2 f}{\partial a_{1i}\partial a_{2i}}\right)^2\right] > 0$ as given by the first two conditions above, $f_{a_{1i}a_{2i}} = \frac{\partial^2 f}{\partial a_{1i}\partial a_{2i}}$ and $f''_{a_{2i}} = \frac{\partial^2 f}{\partial a_{2i}^2} < 0$. It follows that

- If $f_{a_{1i}a_{2i}} = 0$, there is no relationship among effort types, a_{1i} is determined only by equation A.8, and we are back to the model outlined in Section 2;
- If $f_{a_{1i}a_{2i}} < 0$, workers efforts are substitutes in production, the right hand side of equation A.10 is negative, and $\partial a_{1i}/\partial\alpha < 0$;
- If $f_{a_{1i}a_{2i}} > 0$, workers efforts are complements in production, then $\partial a_{1i}/\partial\alpha < 0$ iff $0 < \theta_i < \frac{-f''_{a_{2i}}}{f_{a_{1i}a_{2i}} - f''_{a_{2i}}} < 1$.

Taking the derivative of equation A.10 with respect to s and considering condition 3 above we get:

$$\frac{\partial^3 f}{\partial a_{1i}^2\partial s} f''_{a_{2i}}\frac{\partial a_{1i}}{\partial \alpha} + \Gamma\frac{\partial^2 a_{1i}}{\partial\alpha\partial s} = 0 \tag{A.11}$$

From which we can obtain the same predictions we have in Section 2 as given by

- If $\partial^3 f/\partial a_{1i}^2\partial s > 0$, then $\partial^2 a_{1i}/\partial\alpha\partial s < 0$;
- or, if $\partial^3 f/\partial a_{1i}^2\partial s < 0$, then $\partial^2 a_{1i}/\partial\alpha\partial s > 0$.

We can follow the same procedure to get the comparative statistics with respect to θ_i. Starting again from the first order conditions, taking derivatives we get:

$$\frac{\partial^2 f}{\partial a_{1i}^2}\frac{\partial a_{1i}}{\partial \theta_i} + \frac{\partial^2 f}{\partial a_{1i}\partial a_{2i}}\frac{\partial a_{2i}}{\partial \theta_i} = \frac{1}{\alpha} \tag{A.12}$$

$$\frac{\partial^2 f}{\partial a_{1i} \partial a_{2i}} \frac{\partial a_{1i}}{\partial \theta_i} + \frac{\partial^2 f}{\partial a_{2i}^2} \frac{\partial a_{2i}}{\partial \theta_i} = \frac{1}{\alpha} \tag{A.13}$$

Clearing $\partial a_{2i}/\partial\theta_i$ from equation A.13 and replacing it in A.12 we get

$$\Gamma \frac{\partial a_{1i}}{\partial \theta_i} = \frac{1}{\alpha}(f''_{a_{2i}} - f_{a_{1i}a_{2i}}) \tag{A.14}$$

Conditions 1 and 2 imply that $\partial a_{1i}/\partial\theta_i < 0$ for any value of $f_{a_{1i}a_{2i}}$. Taking derivatives of the previous equation respect to α together with given condition 4 above we obtain

$$\Gamma \frac{\partial^2 a_{1i}}{\partial \alpha \partial \theta_i} = -\frac{(f''_{a_{2i}} - f_{a_{1i}a_{2i}})}{\alpha^2} \tag{A.15}$$

From which follows $\partial^2 a_{1i}/\partial\alpha\partial\theta_i > 0$.

An example of a production function that satisfies all the conditions we have included in this section and is applicable to our setting is $y_i = \frac{1}{s_i}(a_{1i} - a_{1i}^2) + (a_{2i} - a_{2i}^2) + a_{2i}(a_{1i} + s_i) + \epsilon_i$ where $0 \leq s \leq 1$ (as the empirical measure of input quality), and ϵ_i is an error term.

Participation Starting from the expression of the worker's certainty equivalent, we can take its derivative with respect to α and get

$$\frac{\partial \hat{u}}{\partial \alpha} = y_i - a_i + \alpha \frac{\partial y_i}{\partial \alpha} + (1 - \alpha - \theta_i) \frac{\partial a_{1i}}{\partial \alpha} - \theta_i \frac{a_{2i}}{\partial \alpha} - \eta \alpha \sigma^2 \tag{A.16}$$

Since $\frac{\partial y_i}{\partial \alpha} = \frac{\partial f(s_i, a_{1i}, a_{2i})}{\partial a_{1i}} \frac{\partial a_{1i}}{\partial \alpha} + \frac{\partial f(s_i, a_{1i}, a_{2i})}{\partial a_{2i}} \frac{\partial a_{2i}}{\partial \alpha}$ and the worker chooses the optimal effort levels, we can replace the first order condition in equation A.17 and obtain

$$\frac{\partial \hat{u}}{\partial \alpha} = y_i - a_{1i}^* - \eta \alpha \sigma^2 \tag{A.17}$$

Taking the derivative with respect to θ_i, and given $\frac{\partial y_i}{\partial \theta_i} = \frac{\partial f(s_i, a_{1i})}{\partial a_{1i}} \frac{\partial a_{1i}}{\partial \theta_i} + \frac{\partial f(s_i, a_{2i})}{\partial a_{2i}} \frac{\partial a_{2i}}{\partial \theta_i}$, we can replace again the first order condition to get

$$\frac{\partial^2 \hat{u}}{\partial \alpha \partial \theta_i} = -\frac{1 - \theta_i}{\alpha} \frac{\partial a_{1i}}{\partial \theta_i} + \frac{\theta_i}{\alpha} \frac{\partial a_{2i}}{\partial \theta_i} \tag{A.18}$$

where $\frac{\partial a_{1i}}{\partial \theta_i} < 0$ and following the same procedure as in step 2, we can show that $\frac{\partial a_{2i}}{\partial \theta_i} < 0$. Then, $\partial^2\hat{u}/\partial\alpha\partial\theta_i > 0$ if $(\partial a_{1i}/\partial\theta_i)/(\partial a_{1i}/\partial\theta_i + \partial a_{2i}/\partial\theta_i) > \theta_i$. An increase in α increases expected utility on the job relatively more for workers with higher marginal cost θ_i.

Finally, utility on the job also depends on the assigned input quality. It is possible to show that if $\partial^3 f(s_i, a_{1i}, a_{2i})/\partial a_{1i}^2 s_i \geq 0$ then $\partial^2 a_{1i}/\partial\theta_i\partial s_i \leq 0$ but $\partial^2 a_i/\partial\theta_i\partial s_i$ could be positive or negative. Then, we get:

- If $\partial^2 a_{2i}/\partial\theta_i\partial s_i \geq 0$ then $\partial^3\hat{u}/\partial\alpha\partial\theta_i\partial s_i \geq 0$.

- If $\partial^2 a_{2i}/\partial\theta_i\partial s_i \leq 0$ and $(\partial a_{1i}/\partial\theta_i\partial s)/(\partial a_{1i}/\partial\theta_i\partial s + \partial a_{2i}/\partial\theta_i\partial s) > \theta_i$, then $\partial^3\hat{u}/\partial\alpha\partial\theta_i\partial s_i \geq 0$.

Using the same production function suggested before we obtain that $\frac{\partial a_{1i}}{\partial\theta_i} = -\frac{2s}{\alpha(1-s)} < 0$ and $\frac{\partial a_{2i}}{\partial\theta_i} = -\frac{(1+s)}{\alpha(1-s)} < 0$, which implies that $\frac{\partial^2\hat{u}}{\partial\alpha\partial\theta_i} > 0$ if $\theta_i < \frac{2}{3+(1/s)}$. Moreover, $\frac{\partial a_{1i}}{\partial\theta_i\partial\alpha} = \frac{\partial a_{2i}}{\partial\theta_i\partial\alpha} = -2/\alpha(1-s)^2 < 0$, which implies that $\frac{\partial^3\hat{u}}{\partial\alpha\partial\theta_i\partial s_i} \geq 0$ if $\theta_i < 1/2$.

A.4 Threshold for Incentive Pay

This section shows theoretically that the presence of a threshold for piece rate pay does not confound our interpretation of empirical results.

In the presence of a threshold for piece rate pay, equation 4 of Section 2 still defines the optimal level of effort for those workers who achieve the threshold in expectations. For all other workers, exerting effort does not bring any benefit. They will therefore exert a minimum level of effort $\bar{a} < a_i^*$. Let $\tilde{a}_i$ be the level of effort such that worker i reaches the threshold in expectations. The worker will exert effort $\bar{a}$ if $a_i^* \leq \tilde{a}_i$, and a_i^* otherwise.

In our application, the concavity of output with respect to effort is lower when input quality increases, meaning $\partial^3 f(s_i, a_i)/\partial a_i^2 s_i > 0$. In Section 5, we test accordingly whether an increase in α decreases effort relatively more for workers handling inputs of higher quality. The presence of a threshold for incentive pay can potentially confound the interpretation of results if $\partial\tilde{a}_i/\partial\alpha > 0$ and $\partial^2\tilde{a}_i/\partial\alpha\partial s_i > 0$. Under these conditions, an increase in α induces more workers to exert the minimum effort level $\bar{a}$, and relatively more so when input quality is higher.

To explore this possibility, we derive an explicit solution for a_i^* by incorporating the condition $\partial^3 f(s_i, a_i)/\partial a_i^2 s_i > 0$ parsimoniously in a production function of the form

$$y_i = \frac{1}{s_i}(a_i - a_i^2) + \varepsilon_i \tag{A.19}$$

Solving for a_i in the first order condition of the worker's maximization problem in equation 4 of Section 2 yields

$$a_i^* = \frac{1}{2} - \frac{s_i}{2}\left(1 - \frac{1-\theta_i}{\alpha}\right) \tag{A.20}$$

Notice that under the assumption that $1 > \theta_i \geq 1 - \alpha$ we have $a_i^* < 1/2$. Let the threshold for piece rate pay be equal to r. The level of effort $\tilde{a}_i$ such that the worker reaches the threshold in expectations is given by the solution to

$$\frac{\alpha}{s_i}(a_i - a_i^2) + (1-\alpha)a_i = r \tag{A.21}$$

It can be shown that $\partial\tilde{a}_i/\partial\alpha < 0$, and $\partial^2\tilde{a}_i/\partial\alpha\partial s_i < 0$. This means that, as α increases, less workers will exert the minimum effort level $\bar{a}$, and even less so when input quality is higher. The presence of a threshold for piece rate pay would therefore work against us in finding evidence that is consistent with our model predictions.