Workplace Incentives and Organizational Learning∗

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Abstract

This paper studies learning among coworkers when incentives change. We use a simple principal-agent model to show that, when workers are not fully informed on the global shape of the production function, (i) their effort choice changes over time as information is disclosed and processed, and (ii) changing incentives can trigger this learning process. We test this prediction using personnel data from an egg production plant in Peru. Exploiting a sudden change in the contract parameters, we find that workers learn from each other over the shape of the production function. This adjustment process is costly for the firm.

Keywords: organizational learning, workplace incentives, inputs.

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

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1 Introduction

Workers learn from each other. Evidence shows that knowledge sharing between workers can increase productivity and improve organizational performance (Chan et al. 2014; Sandvik et al. 2020; Papay et al. 2020; Menzel 2021), and that the introduction of new products, inputs and technologies can trigger this learning process (Adhvaryu et al. 2021; Atkin et al. 2017). Much less is known about these issues in the context of changing worker compensation. When information is not perfect, changing incentives brings uncertainty. The objective function of agents changes, and so does their optimal decision. The lack of information on all variables evaluated at the new equilibrium generates the scope for learning.

This paper studies learning among coworkers when incentives change, and its implications for firm profitability. Our analysis proceeds in three steps. First, we develop a principal-agent model where an agent’s effort maps into output with noise. The agent does not have full information on the global shape of the production function, and uses output as a signal to update her beliefs over time. Multiple agents observe each other’s effort and output, and learn from each other. Learning is local, and agents only learn about the shape of the production function around a given level of effort. When the contract parameters changes, the optimal effort decision changes as well, generating scope for learning at the new equilibrium.

Second, we take this prediction to the data. We use personnel records from an egg production plant in Peru and exploit a change in workers’ incentive contract parameters for identification. Workers are assigned batches of hens, exert effort to feed them, and collect eggs as output. Workers get a bonus that depends on both total output and food distributed. The weight attached to these performance measures changes over the sampling period, and the optimal feeding effort changes accordingly. We show that workers change their level of effort towards the one exerted by neighboring peers on the previous day upon observing them achieve higher output. This happens only after the announcement of the new contract, around the implementation date, and fades away gradually after 4.5 months.

Third, we quantify the profit losses associated with the incentive change that result from imperfect information and the need of learning. We estimate the amount of food workers would have distributed in the absence of experimentation, and calculate that profits would have been 5 to 6% or USD 340 to 400K higher during the implementation period in the absence of imperfect information over the production function.
This paper contributes to the literature on peer learning at the workplace. Evidence shows that coworkers’ productivity affects own productivity through different mechanisms including technological externalities (Gould and Winter 2009; Arcidiacono et al. 2017), behavioral channels (Kandel and Lazear 1992; Falk and Ichino 2006; Bellemare et al. 2010), the shape of monetary and non-monetary incentives (Bandiera et al. 2005; Mas and Moretti 2009), and knowledge spillovers (Jackson and Bruegmann 2009; Nix 2015; Papay et al. 2020). Some studies provide direct evidence of learning among coworkers within firms. These include Chan et al. (2014) and Sandvik et al. (2020), who study peer learning among salespeople, and Menzel (2021), who finds evidence of knowledge spillovers among workers in Bangladeshi garment factories.

More generally, our study contributes to the literature on organizational learning, which studies the process by which information about products, inputs and technologies is disclosed, exchanged, and processed between and within organizations (Argote 2013). The empirical work in this domain estimates models of learning across firms (Argote et al. 1990; Irwin and Klenow 1994; Benkard 2000; Thornton and Thompson 2001). Others focus on uncertainty about the production function and the profitability and use of new production technologies, a prominent feature of low-income countries (Atkin et al. 2017).

Finally, this paper also contributes to the literature on workplace incentives. In the presence of moral hazard or adverse selection, the provision of incentives is crucial to achieve efficiency and hire and retain the best performing agents (Prendergast 1999). 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 Lazear (2000), a number of studies have shown that performance pay increases output. However, evidence also shows that compensation changes that are perceived to be unfair or adverse by workers can cause shirking, reduced production quality, and higher turnover among highly productive workers, raising costs and limiting managers’ ability to adjust incentives (Krueger and Mas 2004; Mas 2006; Kube et al. 2013; Chen and Horton 2016; Krueger and Friebel 2018; Sandvik et al. 2021). Importantly, the most recent empirical literature has devoted increasing attention to working arrangements in developing countries because of the higher preva-

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1 See Herbst and Mas (2015) for a review of laboratory experiments and field studies of peer effects.
2 The majority of these studies investigate learning among peer farmers, see Foster and Rosenzweig (1995); Munshi (2004); Bandiera and Rasul (2006); Conley and Udry (2010); Hanna et al. (2014); BenYishay and Mobarak (2018); Beaman et al. (2020); Carter et al. (2021).
3 Manso (2011) and Ederer and Manso (2013) study the related problem of how to incentivize innovation in organizations, focusing on managerial compensation and innovation in business strategies.
lence of piece rate pay and the higher labor intensity of the production technology (see for instance Guiteras and Jack 2018).

To the best of our knowledge, ours is the first paper showing that changing incentives can trigger learning within organizations. The lack of a suitable identification strategy prevents us from evaluating the impact of the contract change on equilibrium firm profits. Nonetheless, our study reveals that imperfect information over the shape of the production function can increase the transition costs associated with the implementation of new incentive schemes and personnel management practices in general, possibly explaining low levels of adoption (Bloom and Van Reenen 2007; Bloom et al. 2010; Bloom and Van Reenen 2010; Atkin et al. 2017). We provide an estimate of such adoption costs in the context of a large firm operating in a low-income country using a labor intensive production technology, raising the question of how to manage information within organizations when changing incentives.4

The remainder of the paper is organized as follows. Section 2 outlines the conceptual framework. Section 3 introduces the empirical setting and data respectively. Section 4 illustrates the data, empirical strategy, and results. In Section 5, we estimate the transition cost associated with the contract change. Section 6 concludes.

2 Conceptual Framework

This section illustrates a simple model that formalizes the learning mechanism uncovered by the empirical analysis that follows. Each worker $i$ in period $t$ independently produces output $y_{it}$ combining effort $a_{it}$ with an input of heterogeneous quality $s_{it}$. Output is given by

$$y_{it}(a_{it}, s_{it}) = s_{it} f(a_{it})$$

where $f''_{a}(a_{it}) < 0$ for all $a_i$. Input quality $s_{it}$ is identically and independently distributed across workers. Workers do not observe $s_{it}$, but know its distribution with mean $\mu_s$ and variance $\sigma^2_s$. The global shape of $f(\cdot)$ is also unknown to the worker, who holds in each period beliefs $f_{it}(\cdot)$ over $f(\cdot)$. The combined uncertainty around $s_{it}$ and $f(\cdot)$ is responsible for the inability of the worker to disentangle the separate contribution of effort and input quality to output. It follows that output is only an imprecise signal of the shape of the $f(\cdot)$ function at a given level of effort, generating the scope for learning.

4The production technology of egg production establishments in high-income countries is typically much less labor intensive. For instance, they use automatic feeders and automated gathering belts for egg handling and collection.
The worker’s utility cost of effort is given by $C(a_{it}) = \theta a_{it}^2/2$ with $0 < \theta < 1$. Management observes both output and effort, and motivates the worker by setting the wage equal to

$$w(y_{it}, a_{it}) = \kappa + \alpha y_{it} + (1 - \alpha) a_{it}$$

where $\kappa$ is fixed and $\alpha$ is the weight attached to output relative to effort in compensation. 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. This contract matches the one we observe in our empirical application, and we take it as given. Notice however that using a performance measure that captures worker’s effort along a particular dimension is a common feature in many working environments, especially when workers make decisions regarding the use of some inputs.\footnote{Amodio and Martinez-Carrasco (2020) show that using performance measures linked to one specific dimension of the effort can be optimal in a multitasking setting. Moreover, rewarding the worker for output and effort can be optimal if the worker is risk averse. This is because the two metrics are both informative of worker’s choice, but vary in the amount of risk they impose on the employee, and enter the principal’s payoff in different ways (H¨olmstrom 1979; Baker 1992). As explained later, assuming that workers are risk averse does not change the model predictions and comparative statics.}

We assume that the worker is risk neutral, has utility

$$u_{it} = \kappa + \alpha y_{it} + (1 - \alpha) a_{it} - \theta a_{it}^2$$

and chooses the effort level $a_{it}$ that maximizes her expected utility. Given the expected value $\mu_s$ of input quality and worker’s belief $f_{it}(\cdot)$ on the production function, taking the first order condition we get

$$\alpha \mu_s f'_{it}(a_{it}) + (1 - \alpha) = \theta a_{it}$$

which implicitly defines the optimal level of effort $a^*_{it}$. This changes with the wage contract parameter $\alpha$. Applying the implicit function theorem we get

$$\frac{\partial a^*_{it}}{\partial \alpha} = \frac{\mu_s f'_{it}(a_{it}) - 1}{\theta - \alpha \mu_s f''_{it}(a_{it})}$$

from which it follows that the level of effort may increase or decrease with $\alpha$ depending on whether its expected marginal product $\mu_s f'_{it}(a_{it})$ is higher or lower than one. This is because the marginal wage gains from effort change with $\alpha$. If the expected marginal product of effort is higher than one, the marginal wage gains from effort increase, and so does the optimal choice of effort. The opposite holds if the expected marginal product
of effort is lower than one.\footnote{Assuming risk averse agents yields similar results. Assuming a CARA utility function and $s_{it}$ normally distributed, working in terms of certainty equivalent we obtain the first order condition

$$\alpha \mu s f_{it}'(a_{it}) + (1 - \alpha) = \theta a_{it} + \eta f_{it}(a_{it})a_{it}^2$$

where $\eta$ is the agent’s level of risk aversion. The comparative statics with respect to $\alpha$ remains unchanged.}

Upon exerting effort, the worker observes in each period the corresponding output realization $y_{it} = s_{it} f(a_{it}^*)$. She uses output as signal to update her beliefs over the marginal product of effort in the vicinity of $a_{it}^*$. In order to see this, consider a Taylor series expansion approximation of $f(\cdot)$ at 0 and assume without loss of generality $f(0) = 0$. We have

$$y_{it} \approx s_{it} f'(a_{it}^*)a_{it}^*$$

It follows that, given her choice of effort $a_{it}^*$ at time $t$, when the worker observes a higher than expected output realization – i.e., $s_{it} f'(a_{it}^*)a_{it}^* > \mu s f_{it}'(a_{it}^*)a_{it}^*$ – she acknowledges that there is a positive probability that the true marginal product of effort $f'(\cdot)$ in the vicinity of $a_{it}^*$ is higher than her belief $f_{it}'(\cdot)$. This will lead the worker to revise upwards her beliefs on $f_{it}'(\cdot)$. The opposite holds if the worker observes a lower than expected output realization.\footnote{Notice that it is possible to characterize this process as standard Bayesian updating upon taking logs of equation 6 and assuming that $s_{it}$ is log-normally distributed.}

The objective of the worker is to maximize utility. If the effort cost parameter $\theta$ is low enough, higher output maps into higher utility. It follows that the optimal effort choice will change in the same direction of $f_{it}'(\cdot)$: effort will increase in the next period if output is higher than expected, and decrease otherwise. The magnitude of the change will depend on the wage contract parameter $\alpha$.

If the effort choice and output of coworkers are observable, the worker will also use this information in her learning process. Specifically, given worker $j$’s effort choice $a_{jt}$, worker $i$ has expectation $y_{jt}^i$ on $j$’s output that is based on $i$’s beliefs, i.e. $y_{jt}^i = \mu s f_{jt}(a_{jt})$. Whenever $a_{jt}^* \neq a_{jt}$, such expected output – and corresponding utility – is lower than the one associated with $a_{jt}^*$, as this is the optimal choice of $i$ given her beliefs $f_{it}'(\cdot)$. As a consequence, when worker $i$ observes a realization of coworker’s output that is higher than her own, $y_{jt} > y_{it}$, she will update her beliefs over $f'(\cdot)$ and change her level of effort in the next period towards the one exerted by the coworker in the current period.

The model assumes that workers do not have full information on the global shape of $f(\cdot)$. Assuming risk averse agents yields similar results. Assuming a CARA utility function and $s_{it}$ normally distributed, working in terms of certainty equivalent we obtain the first order condition

$$\alpha \mu s f_{it}'(a_{it}) + (1 - \alpha) = \theta a_{it} + \eta f_{it}(a_{it})a_{it}^2$$

where $\eta$ is the agent’s level of risk aversion. The comparative statics with respect to $\alpha$ remains unchanged.
the production function, and can gain local knowledge through experience and experimentation. In other words, workers can get to know the shape of $f(\cdot)$ in an interval around a specific level of effort $a_{it}$. Yet, this is not necessarily informative of the shape of $f(\cdot)$ at a sufficiently distant level of effort. A change in $\alpha$ changes the optimal choice of effort, brings the workers to operate in a new, unexplored portion of the production function, and triggers learning over the shape of $f(\cdot)$ at the new equilibrium. This is the hypothesis that we take to the data.

Management observes both output and effort. If management were fully informed about the shape of the $f(\cdot)$ function and knew the moments of the input quality $s_{it}$ distribution, it could communicate to the workers and require from them the level of effort $a_{it}$ that maximizes the firm’s payoff. The threat of dismissal would work as an incentive device, and there would be no need of an incentive wage schedule like the one we observe and define in equation 2. In practice, however, workers may be able to partially observe input quality or other idiosyncratic determinants of output that matter for determining the optimal effort level. This informational advantage held by the worker prevents management from writing a contract that specifies the level of effort to exert. Notice that this does not meaningfully change the learning mechanism described in the model: the worker will discount the known pieces of information accordingly, but residual uncertainty over input quality still generates the scope for learning.

Finally, we acknowledge the possibility that other factors may make learning from coworkers and their choices more difficult than learning from own experience. For instance, monitoring peer choices may be costly. Career concerns may induce workers to hide their actions or sabotage their peers. Also, to the extent to which management monitors group output, workers may free ride on each other (Mas and Moretti 2009; Amodio and Martinez-Carrasco 2018). All these mechanisms would make learning from coworkers more difficult and harder to detect empirically with the identification strategy that we present later in Section 4.3.

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8See Laffont and Martimort (2002) on “false moral hazard” models, where the worker’s effort choice is a deterministic function of a non-stochastic output component, and a complete mapping therefore exists between the latter and output.

9For instance, as we show in Amodio and Martinez-Carrasco (2018), we can let $s_{it} = r_{it} \varepsilon_{it}$ with $r_{it}$ being known and $\varepsilon_{it}$ being unknown to the worker, who will then use $y_{it}/r_{it}$ as signal in learning about the $f(\cdot)$ function.
3 The Setting

In the empirical analysis, we use personnel data from a Peruvian egg production plant. Production takes place in different sectors. Each sector comprises different sheds, long-building facilities grouping one to four production units. Online Appendix Figure A.1 shows the picture of a shed that hosts four production units as an example.

Each worker is assigned to a given production unit and assigned a batch of laying hens. The batch as a whole is treated as a single input, as all hens within the batch are bought 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 to the same worker for their entire productive life. Hen productivity varies over time depending on hens’ age and idiosyncratic productivity shocks that materialize throughout their egg-laying span that lasts approximately one year. These shocks pertain the hen themselves (e.g. diseases or weight loss and gain), but also the weather or soil characteristics, or other determinants of output that can be partially known to the worker.

Output is measured by the number of eggs collected during the day. This is a function of both hen characteristics and worker’s effort. Workers exert effort along three main dimensions: hen feeding, egg collection and storage, and cleaning and maintenance of the unit facilities. Feeding the hens is the worker’s primary task. The firm pays for food, but distributing it is costly for the worker because she has to carry around multiple 50kg sacks of food each day and even it out among all hens. The amount of food distributed is decided by the worker. 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 use during the day. This is observed by management, which records information on both the number of sacks of food distributed – measured in half units – and the number of egg boxes collected by the worker during the day. Collecting eggs is also costly for the worker because eggs may break if not handled with care.

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 a separate small warehouse for food and egg storage, clearly visible in Online Appendix Figure A.1. Importantly, the spatial arrangement of production units and warehouses is such that workers can observe their neighboring peers, the number of sacks of food they distribute, and the number of egg boxes they collect each day.
**Changing Incentives**  Workers 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. The formula to calculate the bonus changed over time. In the first period, the bonus payment was 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, each box containing 360 eggs. If this quantity exceeded a given threshold, a piece rate was awarded for each unit above the threshold. On 24 February 2012, the company adopted a new bonus formula, which has been maintained thereafter. This is now based on the number of boxes of eggs collected only. That quantity is multiplied by two, and a piece rate is awarded for each unit above a given threshold. Both the piece rate parameter and the threshold were kept 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 \( y_{it} \), while the number of sacks of food distributed is a measure of worker’s effort \( a_{it} \). 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.

When asked about the reason for changing incentives, management claims that workers were distributing “too much food” under the earlier incentive scheme. At the same time, managers observed a close correspondence between the number of egg boxes and sacks of food distributed. They therefore did not expect the bonus paid to workers to change meaningfully with the new contract, which does not reward workers for food distribution but doubles the piece rate on the number of egg boxes. We show later that the implementation of the new contract manages to reduce the amount of food distributed by workers, in line with management’s expectations and goal.

The change of contract is also indicative of some degree of experimentation on behalf of management. As explained in the end of Section 2, rewarding workers more for output and less directly for feeding effort is efficient if workers hold some informational advantage over management and can tailor effort according to the specific conditions they face. The change of contract suggests that management has some intuitions but is uncertain over the precise extent of this information asymmetry and its consequences for firm output and profits.
4 Empirical Analysis

4.1 Data

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 of contract. Overall, we observe 94 production units, 211 different hen batches, and 127 workers present for at least one day.

Online Appendix Table A.1 shows the summary statistics for the main variables that we use. It does so separately for the overall sample and for the three subsamples as defined by the dates in which the contract change was announced and implemented. Across all periods, workers distribute 23 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. An important determinant of the amount of food distributed is the number of hens assigned to the worker in a given day. The total number of hens per batch is heterogeneous 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 353 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 distributed by the worker, averaging 116 grams per day, with a minimum of 67 and a maximum of 163.

Output is given by the number of eggs collected, averaging more than 8,000 per day. This corresponds to 0.8 daily eggs per hen on average. Consistent with the model, at least part of this variation is attributable to heterogeneity in input quality as hen productivity varies across and within units and batches over time. Part of this variation is informed by the innate characteristics of the hens. When purchased, each batch comes with detailed information on the average number of eggs per week each hen is expected to produce every week as it ages. 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 resources department. Divided by 7, this measure of expected daily productivity varies from 0.02 to 0.93, with an average of 0.82.

The data also provide information on the number of good eggs, which means they can
directly move to the packaging stage, as opposed to the others which may be broken or dirty. This is informative of the speed, time and care devoted to egg collection. We divide the number of good eggs by the total in order to derive a measure of output quality, the average being 86%.

Production units are grouped in 41 different sheds, 35 of them hosting more than one production unit. We calculate for each production unit the average amount of food and the average number of eggs per hen collected in neighboring production units in the same shed on the same day. We complement all this information with a survey that we administered to all workers in March 2013. We are able to use this information in combination with production data for those workers that were still present on the day of the survey, slightly more than 70% of our study sample. We use this survey to elicit information on worker’s tenure at the firm.

### 4.2 Preliminary Evidence

In the model, we assume that output is a concave function of effort. Online Appendix Figure A.2 shows that this is the case empirically. It plots the average number of eggs per hen collected by the worker against the amount of food per hen distributed on the same day, together with its 95% confidence interval. It also plots a kinked linear approximation of the production function. The amount of food at the kink (113.25g) is set to maximize the $R^2$ of a kinked regression of number of eggs per hen over the amount of food distributed. The $R^2$ associated with such a kinked specification is equal to 0.98. For comparison, the one associated with a quadratic polynomial specification is 0.58. Evidence thus shows that a local linear approximation with only one kink provides a very good approximation of the true shape of the production function.

The model also assumes that input quality is at least partially unknown to the worker. To support this assumption, we regress daily output as measured by eggs per hen collected by the worker over the expected productivity measure provided by the batch supplier. The corresponding coefficient estimate is equal to 0.87 and significant at the 1% level. More importantly, this known measure of expected productivity only explains around 45% of the variation in daily output, up to 67% when including the full sets of worker and batch fixed effects, and their interactions that also capture “match effects.” This indicates that idiosyncratic productivity shocks that materialize over the hen life cycle affect their productivity, and that such residual variation in input quality matters.\textsuperscript{10}

\textsuperscript{10}The expected productivity measure is arguably the most informative measure of input quality available to management, possibly shared with the worker. To gain insights on whether workers hold some informational advantage over management regarding input quality, we restrict the sample to the period...
On 29 November 2011, the firm announced that it would implement a new salary structure, changing the weight $\alpha$ attached to output from $\frac{1}{2}$ to 1. The change was implemented on 24 February 2012. Without further restrictions, our model delivers ambiguous predictions on the impact of such change on effort as measured by the amount of food distributed by the worker. Yet, Figure A.2 shows that the slope of the production function is always lower than one. In this case, equation 5 delivers a clear prediction: effort decreases when the weight $\alpha$ attached to output in the bonus formula increases.

Figure 1 shows the average amount of food distributed daily over time during the sample period. The graph shows the smoothed average value together with its 95% confidence interval. The two vertical red lines correspond to the dates of announcement and implementation of the new contract. The amount of food distributed falls discontinuously on announcement and implementation dates, then increases and stabilizes in the later period at a level that is lower than the initial one. This pattern suggests that the new contract was successful in reducing the amount of food distributed by workers, but also that workers may have over-responded initially in the direction suggested by management. It is possible that workers perceived the change as unfair, or that they strategically reduced their feeding effort in anticipation of further changes in the same direction, a variant of the so-called “ratchet effect” – see Laffont and Tirole (1988) – which could interact with the dynamics of learning over time (Carmichael and MacLeod 1993, 2000; Dearden et al. 1990; Cardella and Depew 2018). Notice however that these mechanisms cannot explain the subsequent increase in the amount of food distributed that we observe later in the period. More generally, the pattern shown in Figure 1 could be driven by a variety of factors that affect the production process and workers’ choices differently on each day. We explain in details in the next section whether this is problematic and, in general, the conditions under which the presence of unobserved determinants of workers’ food choice would invalidate our identification strategy.

Online Appendix Table A.1 provides additional evidence of the fall in the amount of food distributed by workers. After the implementation of the new contract, the average amount of sacks of food that workers distribute decreases by more than one, relative to the period before the announcement. This corresponds to a decrease in food per hen of about 7 grams, or 6% of the baseline mean. The table also shows that expected daily productivity as estimated by the hen batch supplier does not change systematically before the announcement of the incentive change and implement a non-parametric kernel regression of the amount of food per hen distributed by the worker over the expected productivity measure. We find that the latter explains only around 37% of the variation in the amount of food distributed, up to 40% when including the full sets of worker and batch fixed effects. We interpret this as evidence that the worker’s choice of effort is shaped by a variety of factors above and beyond what is known to management.
across periods.

Figure 2 plots the distribution of the amount of food per hen distributed by workers in each day and separately for the period before the announcement of the incentive change, between the announcement and implementation date, and after implementation. First, the figure shows how the whole distribution shifts leftwards as the new contract is first announced and then implemented. Second, the distribution is more dispersed in the period between announcement and implementation dates than in the other two periods. When implementing tests on the equality of standard deviations, we can reject at the 1% level the null hypothesis of equal variance. This is suggestive of experimentation during the transition period.

4.3 Identification Strategy

Our hypothesis is that changing incentives triggers learning among workers over the shape of the production function around the new optimal level of effort. As noted before, the spatial arrangement of production units is such that neighboring peers can interact and observe each other. We would therefore expect workers to use the available information on food distributed and output of peers to update their beliefs and inform their own food choice accordingly. This would generate a positive correlation between the choices of neighboring coworkers. But, finding evidence of such correlation does not necessarily mean that workers learn from each other. First, unobserved common factors may independently affect the effort choice of coworkers and tilt them in the same direction. Second, the simultaneous determination of their decisions makes it difficult to identify causal relationships because of the so-called reflection problem (Manski 1993).

To overcome these identification challenges, we adopt a regression framework that builds upon Conley and Udry (2010) and their study of pineapple growers in Ghana. We look at changes in workers’ effort choices over time, and whether they adjust towards their peer choice differentially when the latter achieve higher output. To operationalize this approach, we define for each worker $i$ operating a production unit in shed $g$ on day $t$ the variable

$$M_{igt} = (a_{igt-1} - a_{igt-1}) \times I \{y_{jgt-1} > y_{igt-1}\}$$

where $a_{igt-1}$ is the average effort choice – sacks of food distributed – of neighboring coworkers on the previous day, $a_{igt-1}$ is the effort choice of the worker on that same day, and $I \{y_{jgt-1} > y_{igt-1}\}$ is an indicator of peer relative success, equal to one if the average output – eggs per hen – of neighboring coworkers was higher than own output.
We then implement the following baseline regression specification

\[ \Delta a_{igt} = \beta M_{igt} + \gamma \text{Post}_t \times M_{igt} + X'_{igt} \kappa + \delta_t + \varphi_g + \theta_i + u_{igt} \]  

(8)

where \( \Delta a_{igt} = a_{igt} - a_{igt-1} \) is the change in the effort choice of worker \( i \) from one day to the other, and \( \text{Post}_t \) is a dummy equal to one in the period after the announcement of the new contract. The coefficient \( \beta \) captures whether workers change their level of effort towards the one exerted by neighboring peers on the previous day upon observing them achieve a higher output. \( \gamma \) captures whether this occurs systematically and differentially after the announcement of the new contract. \( \delta_t \) captures day fixed effects, which account for and net out all determinants of food choice that vary over time and affect all workers in the same way. Similarly, \( \varphi_g \) captures shed fixed effects, which account for and net out all determinants of food choice that are common to all workers in a given shed and do not vary over time. We augment the regression specification with worker fixed effects \( \theta_i \) and a vector \( X_{igt} \) of control variables which include the lagged own and coworkers’ input choice and output, the total number of hens in the batch, and a dummy that equals one if expected productivity (estimated by the batch supplier) is above the median. Finally, the term \( u_{igt} \) captures any residual determinants of change in the amount of food distributed. We cluster standard errors along the two dimensions of shed and day to account for unobserved correlation between such residuals across observations belonging to the same shed or day.

A first concern with our identification strategy is that the presence of unobserved determinants of food choice could bias the estimated \( \gamma \). These include strategic considerations on behalf of the workers of the kind discussed in the previous section. However, this would be problematic only insofar as these were systematically related to peer relative success and its indicator nested in the \( M_{igt} \) variable, and if this was differentially the case after the announcement of the new contract.

A second concern is related to “match effects,” meaning the possibility that batches with particular characteristics are assigned to workers that are particularly good or well-suited to handle batches with those characteristics. Once again, this would be problematic only if the productivity of a match was systematically related to own and coworkers’ food choice and peer relative success, and differentially so after the announcement of the new contract.

Finally, following from the discussion in the end of Section 2, notice that costly monitoring, low observability, hidden actions and sabotage would all act in the direction of making learning harder to detect with the proposed strategy. The same holds for
free-riding among workers, as that would generate a negative correlation between peer choices.

Before continuing, we investigate the extent of variation in the $M_{igt}$ variable. Its value is different than zero for around 42% of observations in the sample, and positive (negative) for 23% (19%) of the sample. These relative frequencies are not systematically different across subsamples as defined by whether the observation belongs to before or after the announcement of the new contract, or to workers with lower or higher than median tenure. The $R^2$ of a regression of $M_{igt}$ over the full set of worker fixed effects is equal to 0.47, up to 0.50 when also including all their interactions with the post-announcement dummy. This indicates that $M_{igt}$ varies within workers at least as much as it does between workers.

### 4.4 Results

Table 1 reports the estimated coefficients from equation 8. Column 1 shows the estimated $\beta$ from a regression specification that only includes $M_{igt}$ together with day and shed fixed effects. The estimated $\beta$ is positive and significant at the 1% level. In column 2, we augment the specification with the vector of controls $X_{igt}$. The estimated $\beta$ doubles in magnitude, and remains highly significant. From column 3 onwards, we include the interaction between the $M_{igt}$ variable and the post-announcement dummy.\(^{11}\) The estimated $\beta$ is now close to zero and insignificant while the estimate of $\gamma$ is positive and significant at the 5% level, and becomes significant at the 1% level upon adding worker fixed effects in column 4. Evidence thus supports the hypothesis that learning among coworkers occurs only after the announcement of the new contract.

To gauge the magnitude of the estimated $\gamma$, Online Appendix Figure A.3 plots the distribution of the difference between the average amount of food distributed by neighboring coworkers and the one distributed by the worker on the previous day, $a_{jgt-1} - a_{igt-1}$. This has a standard deviation of 11.30. The change in the amount of food distributed by a given worker from one day to the other, $a_{igt} - a_{igt-1}$, has a standard deviation of 0.619. According to the results in column 4, in the post-announcement period and conditional on peers achieving a higher output, a one standard deviation increase in the difference between coworker’s and own choice of food on the previous day leads to a daily change in own food distributed of 11% of a standard deviation.

In order for workers to learn from each other, they must be able to observe each other’s

\(^{11}\) Notice that the post-announcement dummy itself is not included as its variation is absorbed by the full set of day fixed effects.
choice of feeding effort and the resulting output. Workers in non-neighboring production units can hardly interact or observe each other. If valid, our identification strategy should provide no evidence of learning between them. To check whether this is the case, we define a variable that is constructed as \( \tilde{M}_{igt} \) but considers the average effort choice and output of coworkers in non-neighboring production units. In column 5 of Table 1, we augment our main regression specification with \( \tilde{M}_{igt} \) and its interaction with the post-announcement dummy.\(^{12} \) The estimated coefficients of both variables are insignificant at standard levels. This confirms that observability between workers plays a crucial role for learning.

As explained earlier, when hen batches are moved to production they are assigned to a given production unit and to the same worker for their entire productive life. The extent of unobserved variation in input quality is likely to decrease over time, implying that the scope for learning is biggest among workers handling a newly assigned batch. We test this hypothesis by separately implementing our main regression specification in two subsamples defined according to whether the time elapsed since the current batch was assigned to the worker is less or more than one month. Columns 6 and 7 of Table 1 report the corresponding coefficient estimates. The estimated \( \gamma \) is insignificant while \( \beta \) is highly significant in both cases, but the magnitude of the latter is more than three times higher for workers handling a newly assigned batch than for the other workers. The difference between the two coefficients is significant at the 5% level. Evidence supports the hypothesis that the scope for learning is biggest when a new batch is assigned to the worker, and uncertainty over input quality is largest.

In columns 8 and 9 of Table 1, we implement the regression specification in column 4 separately for the subsample of production units assigned to workers with lower and higher than median tenure. The estimated \( \gamma \) is significant only for workers with high tenure. While surprising at first, we interpret this as evidence that workers with longer experience are more capable of monitoring their peers, elaborate the information that becomes available, and act accordingly.

To conclude, we test whether changes in feeding effort are systematically related to changes in other dimensions of effort, such as the speed, time or care devoted to egg collection, that can potentially relate to output quality. We do so by replacing the dependent variable in our main regression specification with the observed change from one day to the next in the percentage of good eggs over the total number of eggs collected. We report in column 10 of Table 1 the estimated \( \beta \) and \( \gamma \), which are in this case both

\(^{12}\text{For this purpose, the sample is restricted to workers located in sheds with more than two production units as the others do not have non-neighboring coworkers in the same shed.}\)
indistinguishable from zero. This rules out any systematic change in output quality and other dimensions of effort.

We obtained the previous estimates pooling together all observations belonging to the pre and post-announcement period, showing how learning materializes only after the announcement of the new contract. At the same time, we would expect learning to occur only for a limited amount of time. We thus augment the regression specification in equation 8 with all interactions of $M_{igt}$ with a set of dummies that identify each two-week pay period. We omit and use the pay period when the contract change was announced as the reference period. Figure 3 plots the coefficient estimates associated with these interaction terms over time, together with their 95% confidence intervals. The two vertical red lines correspond to the periods of announcement and implementation of the new contract. Estimates are, for the most part, not significantly different from zero for the whole period before the announcement of the new contract. They become positive and significant at the 5% level shortly before implementation, increase in magnitude and then decrease while remaining significant for several periods, then return to being insignificant. We interpret this pattern as evidence that learning was absent prior to the announcement of the new contract, spiked around the implementation date, and faded away gradually after 4.5 months. When comparing Figure 3 with Figure 1, we can see that the two align remarkably well, with the estimates capturing learning among coworkers being insignificant when the food choice is stable, and significant over the adjustment period.

5 The Cost of Learning

In this section, we summarize our attempt to quantify the profit losses associated with the contract change and due to imperfect information and need of learning. We provide the full details of the estimation procedure in Online Appendix A.2.

The fundamental challenge is that we do not observe the counterfactual, i.e. what would have happened to feeding effort, output, and profits in the presence of complete information. That is, we cannot disentangle the variation in the variables of interest that is driven by learning and experimentation from the one determined by idiosyncratic shocks such as changes in output and input prices.

We address this challenge as follows. In the first step, we filter out variation in food choice across sheds, workers and batches by regressing the amount of food per hen distributed by the worker over the corresponding three sets of fixed effects. We then
split the sample in three periods: the one before the announcement of the new contract, the one during which learning occurs, and the one after. The length of the second period is informed by Figure 3 and given by those two-week intervals in which the estimated coefficient capturing knowledge spillovers is positive and significant. Notice that the date of the implementation of the new contract falls within this second period.

In the second step, we use the estimated residuals from the first step to derive the average residual of food distributed per hen in the three periods. We consider the averages in the first and last period as informative of the equilibrium level of feeding effort under the old and new contract respectively.

In the third and last step, we estimate the counterfactual feeding effort choice during the adjustment period by re-centering the distribution of residuals as follows. We subtract the average of the period and add the average of the first period to all observations prior to the implementation date, and do the same using the average of the third period to those after the implementation date. In other words, we re-center the observed distribution of residual food choice in the second period using the averages in the first and third period for the days before and after the implementation of the new contract respectively. Finally, we add to these counterfactual residuals the fixed effects estimated in the first step and obtain the counterfactual choice of food distributed. Not surprisingly given the way we obtain the counterfactual, actual and counterfactual variables differ only in the second period, with the counterfactual amount of food distributed being higher in the absence of experimentation.

Upon obtaining the counterfactual amount of food distributed, we can derive counterfactual output, revenues, food costs, and bonuses paid to the workers. We implement a regression of eggs per hen over the kinked function of food per hen specified in Section 4, and the full set of day, production unit, and batch fixed effects. We then use the estimated coefficients and the counterfactual food per hen to obtain counterfactual output. We calculate revenues using the information on output prices that the firm made available to us. Similarly, we calculate food costs using the information on the price of a sack of food. We use the actual compensation formula before and after the contract change to calculate the bonuses paid to employees. Finally, we combine all this information to calculate profits. Figure 4 shows the corresponding results. The area between the two lines measures the total profit loss over the learning period.13

To get a sense of the uncertainty surrounding these estimates, we implement a bootstrap-

13Online Appendix Figures A.4 and A.5 show the smoothed averages of all estimated actual and counterfactual variables used to calculate profits.
type procedure sampling with replacement from the full dataset and repeating all steps described above 200 times. Online Appendix Table A.2 shows the results from this exercise for each of the variables we use to calculate profits, with standard deviations in parentheses. We estimate a revenue loss of USD 560K and a profit loss of USD 373K. According to our calculations, profits would have been 5.5% higher over the learning period in the presence of complete information on the global shape of the production function. The source of this profit loss lies in the workers’ initial over-response to the contract change. In line with management’s expectations, workers decrease the amount of food distributed, but to the detriment of output and revenues. Over time, workers learn the true shape of the production function around the new equilibrium: their feeding effort choice increases and stabilizes at a level that is lower than the one observed prior to the contract change.

6 Conclusions

This paper shows that changing incentives triggers learning among coworkers within firms. We present a principal-agent framework that illustrates how a change in the contract parameters can trigger learning and experimentation over a new, unexplored portion of the production function. We take this hypothesis to the data using personnel records from a Peruvian egg production plant. We show that workers change their level of effort towards the one exerted by neighboring peers on the previous day upon observing them achieve a higher output, which we interpret as evidence of learning among coworkers. The learning process lasts around 4.5 months, and brings about estimated profit losses of USD 340 to 400K.

The transition costs we estimate suggest that varying degrees of information completeness and associated costs have the potential to explain part of the variation we observe across firms within and across countries in the adoption of incentive pay and personnel management practices in general. Moreover, our findings raise the question of what is the most efficient way to introduce changes in worker compensation and if it is possible to reduce the time and cost of adoption by managing the flow of information between workers (Sandvik et al. 2020). Understanding the conditions under which this is the case is an open question that we leave for future research.

14Online Appendix Figure A.6 shows the distribution of absolute and relative profit gains across the 200 repetitions.
References


Argote, L. (2013). *Organizational Learning*. Springer US.


**Exhibits**

![Figure 1: Food Choice Over Time](image)

**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. The two vertical lines correspond to the dates of announcement and implementation of the new contract. 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.
Notes. The figure plots the smoothed kernel density of grams of food per hen distributed in each day across workers and separately in the period before, during, and after the implementation of the contract change. The figure shows, first, that the entire distribution shifts leftwards as the new contract is first announced and then implemented. Second, the distribution is more dispersed in the period between announcement and implementation dates than in the other two periods: results from tests on the equality of standard deviations indicate that we can reject at the 1% level the null hypothesis of equal variance.
Table 1: Incentive Change and Learning Estimates

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<td></td>
<td>(1)</td>
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<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
<td>(8)</td>
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<td>(10)</td>
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<td>$M_{igt}$</td>
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<td>0.0025***</td>
<td>-0.0007</td>
<td>-0.0013</td>
<td>-0.0028</td>
<td>-0.0080</td>
<td>-0.0030</td>
<td>-0.0011</td>
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<td>0.0025</td>
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<td>(0.0008)</td>
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<td>(0.0016)</td>
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<td>(0.0023)</td>
<td>(0.0027)</td>
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<tr>
<td>$Post_t \times M_{igt}$</td>
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<td>0.0070***</td>
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<td>(0.0020)</td>
<td>(0.0021)</td>
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<td>Yes</td>
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<td>0.1575</td>
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<td>0.1999</td>
<td>0.0686</td>
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</table>

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. The dependent variable in columns 1 to 9 is the change in the amount of food distributed by the worker from the day before to the day of observation, as measured by the change in the number of 50kg sacks distributed, i.e., $a_{igt} - a_{igt-1}$. The dependent variable in column 10 is the change in the percentage of good eggs over the total number of eggs collected over the same period. $M_{igt}$ is equal to the interaction of difference between the average amount of food distributed by neighboring coworkers and the one distributed by the worker on the previous day, $a_{jgt} - a_{igt-1}$, with a dummy equal to one if neighboring coworkers achieved higher average output (eggs per hen), [y_{jgt-1} > y_{igt-1}]. $Post_t$ is a dummy equal to one for all observations belonging to the period after the announcement of the contract change. The vector of other controls includes: the amount of food distributed by the worker and the average of neighboring coworkers on the previous day, $a_{igt-1}$ and $a_{jgt-1}$; their output, $y_{igt-1}$ and $y_{jgt-1}$; the total number of hens in the batch; a dummy equal to one when expected productivity (as estimated by the batch supplier) is higher than the median. In column (5), $\tilde{M}_{igt}$ is constructed using information on the amount of food distributed by non-neighboring coworkers in the same shed and their output, and the sample is restricted to workers located in sheds with more than two production units as the others do not have non-neighboring coworkers in the same shed. In columns (6) and (7) the sample is split according to whether the time elapsed since the current batch was first assigned to the worker (match duration) is lower or higher than one month. In columns (8) and (9) the sample is split between workers with lower and higher than median tenure respectively, and restricted to those observations that we can merge with the survey of workers that we administered in March 2013.
Figure 3: Incentive Change and Learning Over Time

Notes. The figure plots the coefficient estimates associated with the whole set of interactions between the $M_{igt}$ variable specified in Section 4.3 and a dummy for each two-week pay period. Estimates are obtained from an augmented version of regression specification in equation 8 that includes all these interactions. The two vertical lines correspond to the periods of announcement and implementation of the new contract. The announcement pay period is used as reference. The coefficient estimate that captures learning among coworkers increases after the announcement and becomes positive and significant around and after the implementation date, consistent with Figure 1.
Notes. The figure shows the estimated actual and counterfactual smoothed average profits per day. The estimation is described in Section 5 and Online Appendix A.2. The first two vertical lines indicate the period of announcement and implementation of the incentive change respectively, while the third one corresponds to the last period in which learning occurs according to the results depicted in Figure 3.
## Appendix for Online Publication

### A.1 Additional Tables and Figures

#### Table A.1: Summary Statistics

<table>
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<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
<th>N</th>
</tr>
</thead>
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<tr>
<td>Food Distributed (50kg sacks)</td>
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<td>41134</td>
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<td>Expected Productivity</td>
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<td><strong>Panel B – Before Announcement</strong></td>
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<td>Food Distributed (50kg sacks)</td>
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<td><strong>Panel C – Between Announcement and Implementation</strong></td>
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<td>Total Eggs Collected</td>
<td>7990.277</td>
<td>3546.735</td>
<td>0</td>
<td>15131</td>
<td>22169</td>
</tr>
<tr>
<td>Total Eggs per Hen</td>
<td>0.791</td>
<td>0.19</td>
<td>0</td>
<td>1</td>
<td>22169</td>
</tr>
<tr>
<td>Percentage of Good Eggs</td>
<td>85.927</td>
<td>8.673</td>
<td>0</td>
<td>100</td>
<td>22068</td>
</tr>
<tr>
<td>Expected Productivity</td>
<td>0.822</td>
<td>0.13</td>
<td>0.02</td>
<td>0.934</td>
<td>21687</td>
</tr>
</tbody>
</table>

Notes. The table reports the summary statistics of the variable used in the empirical analysis in the overall sample and separately for the period before, during, and after the contract change.
Table A.2: Counterfactual Estimates

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>Simulation</th>
<th>Difference</th>
<th>% Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Eggs (Millions)</td>
<td>374.084</td>
<td>379.210</td>
<td>5.126</td>
<td>0.014</td>
</tr>
<tr>
<td>Revenues (USD Millions)</td>
<td>38.860</td>
<td>39.419</td>
<td>0.560</td>
<td>0.014</td>
</tr>
<tr>
<td>Food (Millions of 50kg sacks)</td>
<td>1.077</td>
<td>1.090</td>
<td>0.013</td>
<td>0.012</td>
</tr>
<tr>
<td>Food Cost (USD Millions)</td>
<td>17.816</td>
<td>18.001</td>
<td>0.186</td>
<td>0.010</td>
</tr>
<tr>
<td>Bonuses (USD Millions)</td>
<td>0.018</td>
<td>0.019</td>
<td>0.002</td>
<td>0.089</td>
</tr>
<tr>
<td>Profits (USD Millions)</td>
<td>21.026</td>
<td>21.399</td>
<td>0.373</td>
<td>0.018</td>
</tr>
<tr>
<td>Profits Adj. Period (USD Millions)</td>
<td>6.754</td>
<td>7.126</td>
<td>0.373</td>
<td>0.055</td>
</tr>
</tbody>
</table>

Notes. The table shows the average and standard deviation of estimated actual and counterfactual variables. Both are estimated with the procedure described in Section 5 and Online Appendix A.2. Distributions are obtained by implementing a bootstrap-type procedure of resampling with replacement in 200 repetitions.
Figure A.1: Production Units

Notes. The picture of a particular shed hosting four production units. Each production unit is defined by one worker and the batch of laying hens assigned to him. We can distinguish in the picture the four production units’ warehouses located across the trail from the shed.
**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 also plots a kinked linear approximation of the production function. The values of amount of food at the kink (113.25g) is chosen in order to maximize the $R^2$ of a kinked regression of number of eggs per hen over the amount of food distributed.
Figure A.3: Distribution of Food Choice Differences among Coworkers

Notes. The figure plots the distribution of the difference between the average amount of food distributed by neighboring coworkers and the one distributed by the worker on the previous day, $a_{igt-1} - a_{igt-1}$. 
Figure A.4: Estimated Actual and Counterfactual Output and Revenues

Notes. The top figure shows the estimated smoothed average of the total number of eggs collected, and its counterfactual in a simulated environment with no learning. The bottom figure shows the estimated actual and counterfactual amount of revenues per day. The procedure to construct these counterfactuals is described in Section 5 and Online Appendix A.2. The first two vertical lines indicate the period of announcement and implementation of the incentive change respectively, while the third one corresponds to the last period in which learning occurs according to the results depicted in Figure 3.
Figure A.5: Estimated Actual and Counterfactual Food Choice and Wages

Notes. The top figure shows the actual smoothed average of the amount of food distributed by workers, and its counterfactual in a simulated environment with no learning. The bottom figure shows the estimated smoothed average of bonuses paid and its counterfactual. The procedure to construct these counterfactuals is described in Section 5 and Online Appendix A.2. The first two vertical lines indicate the period of announcement and implementation of the incentive change respectively, while the third one corresponds to the last period in which learning occurs according to the results depicted in Figure 3.
Figure A.6: Distribution of Profit Gains

Notes. The top figure shows the distribution of overall profit gains in the absence of learning. The bottom figure shows the percentage change in profits over the adjustment period, between the date of announcement of incentive change and the last period in which learning occurs according to the results depicted in Figure 3. Predictions and counterfactuals are estimated with the procedure described in Section 5 and Online Appendix A.2. Both distributions are obtained after a bootstrap procedure of resampling with replacement in 200 repetitions.
A.2 Counterfactual Estimation

In this section, we provide the full details of the counterfactual estimation procedure summarized in Section 5.

In the first step, we implement the following regression specification

\[ h_{igt} = \theta_i + \varphi_g + \psi_b + \varepsilon_{igt} \]  

where \( h_{igt} \) is the amount of food per hen distributed by worker \( i \) who is assigned batch \( b \) operating a production unit in shed \( g \) on day \( t \) while \( \theta_i, \varphi_g \) and \( \psi_b \) stand for worker, shed, and batch fixed effects.

In the second step, we use the estimated residuals from the first step to derive the average residual of food distributed per hen in the periods before the announcement of the new contract, the one during which learning occurs, and the one after. The length of the second period is informed by Figure 3 and given by those two-week intervals in which the estimated coefficient capturing knowledge spillovers is positive and significant. The date of the implementation of the new contract, which we label as \( T \), falls within this second period.

Specifically, let \( \bar{\hat{\varepsilon}}_B \) be the average of \( \hat{\varepsilon}_{igt} \) in the period before the announcement of the new contract, \( \bar{\hat{\varepsilon}}_D \) be the average in the period during which learning occurs, and \( \bar{\hat{\varepsilon}}_A \) be the average in the final period.

In the third step, we use these averages to re-center the distribution of residuals. That is, we obtain counterfactual residuals \( \tilde{\varepsilon}_{igt} \) as

\[ \tilde{\varepsilon}_{igt} = \hat{\varepsilon}_{igt} - \bar{\hat{\varepsilon}}_D + \bar{\hat{\varepsilon}}_B \quad \text{if} \quad t < T \\
\tilde{\varepsilon}_{igt} = \hat{\varepsilon}_{igt} - \bar{\hat{\varepsilon}}_D + \bar{\hat{\varepsilon}}_A \quad \text{if} \quad t \geq T \]  

Finally, we add to these counterfactual residuals the fixed effects estimated in the first step and obtain the counterfactual choice of food distributed per hen \( \tilde{h}_{igt} \) as given by

\[ \tilde{h}_{igt} = \tilde{\varepsilon}_{igt} + \hat{\theta}_i + \hat{\varphi}_g + \hat{\psi}_b \]  

from which we can derive the counterfactual total amount of food \( \tilde{a}_{igt} \) distributed by the worker, i.e. \( \tilde{a}_{igt} = \tilde{h}_{igt} n_{igt} \) where \( n_{igt} \) is the number of assigned hens.

Upon obtaining the counterfactual amount of food distributed, we can derive counterfactual output, revenues, food costs, and bonuses paid to the workers. Consistent with
Section 4, Figure A.2, and given equation 1 above, we implement the following kinked regression specification

\[ y_{igt} = \beta h_{igt} \times I\{h_{igt} < H\} + \gamma h_{igt} \times I\{h_{igt} \geq H\} + \omega_i + \phi_g + \lambda_b + \epsilon_{igt} \] (4)

where \( y_{igt} \) is the number of eggs per hen distributed by worker \( i \) who is assigned batch \( b \) operating a production unit in shed \( g \) on day \( t \). \( h_{igt} \) is the amount of food per hen distributed by the worker, and \( H \) is the kink value, equal to 113.25g. \( \omega_i, \phi_g \) and \( \lambda_b \) stand for worker, shed, and batch fixed effects. We use the estimated coefficients and the counterfactual food per hen \( \tilde{h}_{igt} \) to obtain counterfactual output \( \tilde{y}_{igt} \), i.e.

\[ \tilde{y}_{igt} = \hat{\beta} \tilde{h}_{igt} \times I\{h_{igt} < H\} + \hat{\gamma} \tilde{h}_{igt} \times I\{h_{igt} \geq H\} + \hat{\omega}_i + \hat{\phi}_g + \hat{\lambda}_b \] (5)

Upon obtaining counterfactual output, we use information on output prices that the firm made available to us to calculate actual and counterfactual revenues, i.e. \( r_{igt} = p y_{igt} \) and \( \tilde{r}_{igt} = p \tilde{y}_{igt} \) where \( p \) is the price per egg. Similarly, we use the information on food price to calculate actual and counterfactual food costs, i.e. \( c_{igt} = q a_{igt} \) and \( \tilde{c}_{igt} = q \tilde{a}_{igt} \) where \( q \) is the unit price of food. We also use the actual compensation formula before and after the contract change to calculate actual and counterfactual bonuses paid to employees, equal to \( b(y_{igt}, a_{igt}) = \alpha y_{igt} + (1-\alpha)a_{igt} \) and \( \tilde{b}(\tilde{y}_{igt}, \tilde{a}_{igt}) = \alpha \tilde{y}_{igt} + (1-\alpha)\tilde{a}_{igt} \) respectively with \( \alpha = 1/2 \) before the change, and \( \alpha = 1 \) after the change. Finally, we combine all this information to calculate actual and counterfactual profits \( \pi_t = \sum_g \sum_i \sum_b (r_{igt} - c_{igt} - b_{igt}) \) and \( \tilde{\pi}_t = \sum_g \sum_i \sum_b (\tilde{r}_{igt} - \tilde{c}_{igt} - \tilde{b}_{igt}) \) respectively.

To get a sense of the uncertainty surrounding these estimates, we implement a bootstrap-type procedure sampling with replacement from the full dataset and repeating all steps described above 200 times. Online Appendix Table A.2 shows the results from this exercise for each of the variables we use to calculate profits, with standard deviations in parentheses.