Input Allocation, Workforce Management and Productivity Spillovers: Evidence from Personnel Data*

Francesco Amodio† Miguel A. Martinez-Carrasco‡

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Abstract

This paper shows how human resource management practices and input heterogeneity jointly trigger productivity spillovers at the workplace. In an egg production plant in rural Peru, workers produce output combining effort with inputs of heterogeneous quality. Exploiting quasi-random variation in the productivity of inputs assigned to workers, we find evidence of a negative causal effect of an increase in coworkers' daily output on own output and its quality. We show both theoretically and empirically that the effect captures free riding among workers, which originates from the way the management informs its decisions on whether and who to dismiss. Evidence also suggests that providing monetary and social incentives can offset negative productivity spillovers. Our study and results show that production and human resource management practices interact in the generation of externalities at the workplace. Counterfactual analyses suggest productivity gains from the implementation of alternative input assignment schedules and dismissal policies to be up to 20%.

Keywords: incentives, termination, input heterogeneity, spillovers, productivity.

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

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†francesco.amodio@mcgill.ca, Department of Economics and Institute for the Study of International Development, McGill University, Leacock Building 514, 855 Sherbrooke St. West, Montreal, QC H3A 2T7.

‡miguel.martinez@udep.pe, Department of Economics, Universidad de Piura, Calle Mártir José Olaya 162, Miraflores 15074, Lima, Peru.

1 Introduction

In many workplaces, the productivity of workers is affected by coworkers' productivity. A number of studies analyzing a highly diverse set of occupations provide evidence of these productivity spillovers. In a recent survey of them, Herbst and Mas (2015) show how estimates of productivity spillovers are typically positive and significant, and comparable between laboratory experiments and field studies.

There are several different sources of productivity spillovers at the workplace. First, these may be brought about by the very same nature of the production technology. If coworkers are complements or substitutes in the workplace production function, a change in the effort exerted by coworkers changes the marginal product of effort for the other workers. The production technology of sport teams is a clear example of this kind (Gould and Winter 2009; Arcidiacono, Kinsler, and Price 2015). Second, workers may learn from each other. If that is the case, workers will be more productive when working along highly productive peers (Jackson and Bruegmann 2009; Nix 2015). Third, behavioral considerations may play a role. Indeed, a given worker may find effort less costly to exert at the margin if coworkers exert more effort (Kandel and Lazear 1992; Falk and Ichino 2006). Fourth, a possible source of productivity spillovers lies in the externalities generated by the pay scheme, dismissal policy, or human resource management in general. For example, the implementation of relative performance or team-based evaluation makes the effort choices of coworkers interdependent, even in absence of other sources of externalities (Bandiera, Barankay, and Rasul 2005; Mas and Moretti 2009).

Existing studies explore these issues in settings where output is a (noisy) function of workers' effort only. However, in many workplaces, workers produce output by combining their effort with inputs of heterogeneous quality. In Bangladeshi garment factories, the quality of raw textiles affects the productivity of workers as measured by the number of items processed per unit of time. Likewise, the speed at which warehouse workers fill trucks is affected by the shape and weight of the parcels they handle. Similarly, the amount of time it takes for a judge to close a case depends on her own effort as well as on both observable and unobservable characteristics or complexity of the case itself (Coviello, Ichino, and Persico 2014).

This paper investigates productivity spillovers among workers in settings where the latter handle inputs of heterogeneous quality. The characteristics of inputs individually assigned to workers directly affect their productivity, and, in the presence of any source of externalities, also trigger productivity spillovers among them. Specifically, we focus on the last channel listed above. When workers' evaluation is not (or cannot be) made conditional on the quality of the assigned inputs, the externalities induced by human resource management practices generate productivity spillovers from heterogeneous inputs. Is there any evidence of productivity spillovers of this origin? To what extent does input allocation matter for aggregate productivity at the workplace? Does poor human resource management create the scope for input misallocation within the firm?

Measuring productivity spillovers from heterogeneous inputs is challenging for three main reasons. First, firms often do not maintain records on the productivity of individual workers. Second, even when such data exist, input quality is often unobservable or hard to measure. Finally, in order to credibly identify productivity spillovers from heterogeneous inputs, these inputs and their quality need to be as good as randomly assigned to workers.

We overcome these issues altogether by studying the case of a leading egg producing company in Peru. The production technology and arrangements at its plant are particularly suitable for our analysis. Workers are grouped in several sheds. Each worker is assigned a given batch of laying hens. Hens' characteristics and worker's effort jointly determine individual productivity as measured by the daily number of collected eggs. In particular, variation in the age of hens assigned to the worker induces variation in his productivity. Using daily personnel data, we exploit quasi-random variation in the age of hens assigned to coworkers in order to identify the causal effect of an increase in coworkers' productivity on the productivity of a given worker, conditional on his own hens' age.

We find evidence of negative productivity spillovers. Conditionally on own input quality, workers' productivity is systematically lower when the productivity of neighboring coworkers is exogenously raised by the assignment of higher quality inputs. A positive shift in average coworkers' inputs quality inducing a one standard deviation increase in their daily output causes a given worker's output to drop by almost a third of a standard deviation. We also find output quality to decrease significantly, with the effect in standard deviation units being similar in magnitude to the effect on quantity. We attribute these effects to a change in the level of effort exerted by the worker, which varies systematically with coworkers' productivity.

We argue that the specific source of externalities in this setting lies in human resource management practices, and, in particular, the worker evaluation and dismissal policies implemented by the firm. In our conceptual framework, we build upon Mas and Moretti (2009), and characterize the worker's optimal effort choice. Daily productivity is a signal of the level of effort exerted by the worker, which is unobservable to the management. The latter combines information on individual and coworkers' productivity in evaluating employees and making dismissal decisions. If overall or average productivity positively affect to some extent worker evaluation, an increase in the productivity of coworkers increases a given worker's probability of keeping the job. As a result, workers free ride on each other: when coworkers' productivity increases, individual marginal returns from effort decrease for a given worker, and her optimal effort supply falls accordingly.[1] Workforce turnover information in the data allows us to see how employment termination probabilities correlate with individual and coworkers' productivity, validating the specific mechanism identified by theory.

In the second part of the paper, we study whether and how the provision of incentives can counteract the workers' tendency to free ride and thus offset negative spillovers at the workplace. Rather than asking whether incentives increase workers' productivity, we investigate their effect on the size and sign of productivity spillovers. In our conceptual framework, monetary incentives provide extra marginal benefits from own effort, leveraged by the probability of keeping the job and earn the corresponding salary. By the same token, working along friends induces peer pressure in the form of diminished marginal cost of effort (Kandel and Lazear 1992; Falk and Ichino 2006; Mas and Moretti 2009). As a result, both types of incentives bring about positive externalities among coworkers' in their optimal choice of productive effort, mitigating the previously identified negative effect of coworkers' productivity.

We exploit the specific features of the pay incentive regime in order to evaluate effect heterogeneity according to piece rate incentive exposure. Workers receive extra pay for every egg box they produce above a given threshold. Hens' age affects productivity, so that the probability of reaching the threshold and being exposed to piece rate pay changes for a given worker depending on the age of own assigned hens. Consistent with the above reasoning, we find no effect of coworkers' productivity when the worker is assigned highly productive hens, meaning he is more likely to reach the piece rate threshold and to be exposed to piece rate pay. We also use elicited information on the friendship network among workers to test whether the average effect of coworkers' productivity changes with workers' friendship status. Consistent with the previously outlined peer pressure argument, we do not find any significant effect of average coworkers' daily output when the given worker identifies any of his neighboring coworkers as friends. This finding also allows us to rule out the possibility that the observed average negative effect of coworkers' productivity on own productivity captures the implementation of cooperative strategies among coworkers, which would be even more sustainable among friends.

[1]The opposite holds if the management attaches a negative weight to overall or average productivity in evaluating a single worker, as in relative performance evaluation schemes. We allow our conceptual framework in Section 2 to be general enough to cover all these cases. We discuss the rationale for the implementation of the termination policy we observe at the firm in Section 6.1 and Appendix A.1.

Our case study provides empirical evidence of free riding among coworkers, imputable to the teamwork-type externalities generated by the firm's worker evaluation and termination policy. In this respect, our results add to the literature which investigates the externalities generated by human resource management practices. Bandiera, Barankay, and Rasul (2005) explore the role played by social ties among coworkers in the internalization of negative externalities under relative performance evaluation, and their impact on productivity under individual performance pay (Bandiera, Barankay, and Rasul 2010). Bandiera, Barankay, and Rasul (2007, 2008, 2009) provide direct evidence of the impact of managerial incentives on productivity, and their consequences for lower-tier workers who are socially connected to managers. Bandiera, Barankay, and Rasul (2013) study instead the effectiveness of team-based incentives and their relationship with social connections. Using daily personnel data from a flower processing plant in Kenya, Hjort (2014) shows how the ethnic composition of working teams affects productivity at the workplace, with the negative effect of ethnic diversity being larger when political conflict between ethnic blocs intensifies. He also shows how this effect is mitigated by the introduction of team-based pay.

The conceptual framework in our paper builds upon Mas and Moretti (2009). They study peer effects and productivity among cashiers in a large US supermarket chain, exploiting variation in team composition across ten-minutes time intervals. This allows them to show how the productivity of a given worker changes with coworkers' permanent productivity, with variation in the latter being due to the entry and exit of peers into shifts. The empirical results of the study show that social pressure from observing high-ability peers is the central mechanism generating positive productivity spillovers, and speak against other potential explanation such as prosocial preferences or knowledge spillovers.

To the best of our knowledge, ours represents the first attempt to study how heterogeneous inputs and their allocation to working peers trigger productivity spillovers at the workplace. Our study is thus relevant in that it has implications for several different aspects of both *production* and *human resource management*, ranging from input assignment to worker evaluation, dismissal and incentive regime policies. Indeed, we show how all these elements interact and determine the total amount of externalities in the system and thus overall productivity. In order to shed further light on the issue, we perform a structural estimation exercise based on our conceptual framework. We estimate the unobserved exogenous parameters of the model, and conduct counterfactual policy analyses. Holding everything else constant, we estimate that implementing alternative input assignment schedules would bring about up to 20% productivity gains. By the same token, implementing alternative termination policies would yield productivity gains still around 20%. Related to this, notice that the firm under investigation employs a relatively more labor intensive technology compared to firms in the same sector, but operating in developed countries. Our analysis and results are thus relevant in the microfoundation of productivity-enhancing management practices in developing countries (Bloom and Van Reenen 2007, 2010; Bloom, Mahajan, McKenzie, and Roberts 2010; Bloom, Eifert, Mahajan, McKenzie, and Roberts 2013). In this respect, our paper is close to Hjort (2014) in that it highlights the efficiency cost of input misallocation among workers, and explores how properly designed incentives may partially eliminate these costs. In the context of an Indian garment factory, Adhvaryu, Kala, and Nyshadham (2014) show how the management can reduce the extent of negative productivity shocks by reallocating workers to tasks.

The rest of the paper is organized as follows. Section 2 presents the conceptual framework for the analysis. Section 3 provides the details of the setting. The data and the relevant baseline statistics are presented in Section 4. Section 5 shows the results from the empirical analysis, together with robustness checks and estimates of effect heterogeneity. Evidence on the mechanism at work is presented in Section 6. The impact of monetary and social incentives is discussed in Section 7, while Section 8 presents the counterfactual analyses of alternative input assignment schedules and dismissal policies. Section 9 concludes.

2 Conceptual Framework

The purpose of this section is to illustrate how human resource management practices, and worker dismissal policies in particular, may originate productivity spillovers in a context where workers process inputs of heterogeneous quality. The mechanisms at work can be formalized by means of a simple analytical framework.

N workers independently produce output $y_i \geq 0$ combining effort $e_i \geq 0$ with a given input of quality $s_i \geq 0$, with $i \in \{1, 2, ., N\}$. Effort cost is positive and convex, so that $C(e_i) = ce_i^2/2$ with $c > 0$. Output at a moment in time is given by

$$y_i = f(e_i, s_i) \tag{1}$$

Effort and input quality are complement in production. In particular, let $f(e_i, s_i) = e_i s_i$. Effort is unobservable to the management. Input quality s_i can be thought of as a function of both observable and unobservable input characteristics. We therefore restrict our attention to those cases in which the contribution of input to output is not or cannot be fully netted out by the management. As a result, y_i altogether is a signal of worker's exerted effort.[2]

Let each worker earn a fixed salary ω from which she derives utility $U(\omega)$. Similarly to Mas and Moretti (2009), with probability Q_i the worker keeps her job and earns the corresponding fixed salary. In case the employment relationship terminates, the worker does not earn any salary and derives zero utility. The threat of dismissal works as an incentive device aimed to solve for the moral hazard problem. Indeed, Q_i is set by the management as a function of both individual and coworkers' average output, meaning $Q_i = q(y_i, \bar{y}_{-i})$. The shape of the $q(\cdot)$ function captures the features of the implemented termination policy, together with the externalities it generates among coworkers. We do not rely on any specific functional form, and only assume $q_1(\cdot) > 0$ and continuously differentiable, $q_{11}(\cdot) \leq 0$, and that $q_{12}(\cdot)$ exists. As shown later, this allows to take into consideration several alternative termination policies.

Each worker chooses the effort level $e_i \geq 0$ which maximizes her expected utility

$$\max_{e_i} U(\omega)\ q(y_i, \bar{y}_{-i}) - c\frac{e_i^2}{2} \tag{2}$$

Taking the corresponding first order condition yields

$$U(\omega)\ q_1(y_i, \bar{y}_{-i})\ s_i = ce_i \tag{3}$$

With q_1 continuously differentiable, the implicit function theorem can be applied to the above equation in order to derive how the worker's optimal effort level changes with coworkers' average output, meaning

$$\frac{\partial e_i^*}{\partial \bar{y}_{-i}} = \frac{U(\omega)\ q_{12}(y_i, \bar{y}_{-i})\ s_i}{c - U(\omega)\ q_{11}(y_i, \bar{y}_{-i})\ s_i^2} \tag{4}$$

Notice that the denominator is always positive, and the sign of the above derivative is uniquely determined by the sign of $q_{12}(\cdot)$. The cross derivative of the $q(\cdot)$ function captures how marginal returns from own output in terms of increased probability of keeping the job change with coworkers' average output. Such relationship is built into the termination policy specified by the management.

For instance, forced-ranking procedures or relative performance evaluation schemes in general will let an increase in coworkers' average output positively affect marginal returns from own output. This is the case if $Q_i = q(\alpha y_i - \beta \bar{y}_{-i})$, with $q'(\cdot) > 0$, $q''(\cdot) < 0$ and $0 < \beta < \alpha$. It follows that $q_{12}(\cdot) = -\beta\alpha q''(\cdot) > 0$. In this case, the

[2] One specific example is given in Appendix A, where we also consider the possibility for the principal to net out observable input characteristics in deriving a signal of worker's exerted effort.

worker's optimal level of effort will increase with an increase in coworkers' average output. On the contrary, if total output positively matters to some extent for worker evaluation, teamwork-type externalities will arise. An increase in coworkers' average output decreases marginal returns from own output in this case. At the extreme, one can think at Q_i as being a function of total output only and thus equal for all i, meaning $Q_i = q\left(y_i + (N-1)\bar{y}_{-i}\right)$. This implies $q_{12}(\cdot) < 0$. The worker's optimal effort level will thus fall with an increase in coworkers' average output as workers free ride on each other.

In this framework, the termination policy implemented by the management generates externalities among coworkers in their optimal choice of effort. Workers best-respond to each other in equilibrium.[3] It is worth highlighting that the proposed conceptual background departs from the one in Mas and Moretti (2009) along two relevant dimensions. First, we explicitly model the role of production inputs other than effort. Heterogeneity in their productivity induces variation in both own and coworkers' productivity. Second, we leave the probability of keeping the job function $q(\cdot)$ unspecified along the relevant margin of its cross derivative. We thus consider *a priori* a large family of implementable policies linking own and coworkers' results to termination probabilities.

Monetary and Social Incentives We now illustrate how incentive provision can shape externalities in this context. We are interested in understanding whether sufficiently strong incentives can change the sign and size of productivity spillovers. Social incentives can be framed as *peer pressure*. In its original formulation by Kandel and Lazear (1992), peer pressure operates through the effort cost function: coworkers' effort diminishes the marginal cost of effort for the worker. The theoretical approach in Falk and Ichino (2006) and Mas and Moretti (2009) is built around the same argument. In the context of this paper, output is not only a function of worker's effort, but also of the quality of the assigned input. We thus adopt a slightly modified approach and model peer pressure as operating through a decrease in the cost of effort following an increase in coworkers' output $\bar{y}_{-i}$. Starting from the same framework presented above,

[3]Notice that utility functions are quasi-concave with respect to e_i, the strategy space of workers is convex and the continuous differentiability of $q_1(\cdot) > 0$ ensures best-reply function to exist and be continuous. Hence, the Kakutani fixed-point theorem applies and an equilibrium exists. Indeed, under specific functional forms for $q(\cdot)$, it is possible to solve for the equilibrium of the non-cooperative game workers play and derive closed-form solutions. At equilibrium, the sign of the relationship between own effort and coworkers' input quality is still informed by the sign of the cross derivative $q_{12}(\cdot)$. The intuition for this result goes as follows. An increase in coworkers' input quality increases their effort due to the complementarity between the two in the production function. If $q_{12}(\cdot) < 0$, own effort would simultaneously decrease, inducing coworkers' effort to increase even more, etc. That is, the negative relationship between coworkers' input quality and own effort self-reinforces itself at equilibrium.

the worker's problem becomes the one of choosing effort level $e_i \geq 0$ which maximizes the expected utility

$$\max_{e_i} U(\omega)\, q(y_i, \bar{y}_{-i}) - c\frac{e_i}{2}\,(e_i - \lambda\, \bar{y}_{-i}) \tag{5}$$

where $\lambda > 0$ is a generic parameter capturing the intensity of peer pressure mechanisms. It can be shown that, while the firm's implemented termination policy still generates positive teamwork-type externalities, peer pressure pushes the same in the opposite direction, possibly changing the sign of productivity spillovers.[4]

As for monetary incentives, their impact can also be incorporated within the original framework. For simplicity, let utility $U(\cdot)$ be linear in its argument. We depart from the previous formulation in that the wage now incorporates a piece rate component related to own daily output, meaning $\omega = F + \kappa y_i$ with $\kappa > 0$. As before, the worker chooses the effort level $e_i \geq 0$ which maximizes her expected utility

$$\max_{e_i}\, (F + \kappa y_i) q(y_i, \bar{y}_{-i}) - c\frac{e_i^2}{2} \tag{6}$$

Compared to the fixed-wage case, piece rate incentives provide extra motivation for effort. Notice as well that monetary incentives are leveraged by the probability $q(\cdot)$ of keeping the job. Also in this case, the sign of productivity spillovers is no longer uniquely determined by the sign of the cross derivative $q_{12}(\cdot)$.[5] If the firm's implemented termination policy is such that the latter is negative, own optimal effort may still increase with coworkers' productivity. This is because coworkers' productivity increases the probability of keeping the job. Even if this lowers the marginal impact of own productivity on the probability of keeping the job, it leverages the power of monetary incentives, as these are earned only if the job is kept. The latter effect may dominate the former, yielding positive productivity spillovers.

This basic framework does not incorporate other possible sources of productivity spillovers, such as knowledge spillovers from social learning, monitoring on behalf of supervisors, discouragement from highly productive peers, or the possibility that workers engage in cooperative strategies. Just as we did with our formalization of monetary and social incentives, these may potentially be incorporated in the model without changing its basic intuition on the role of the termination policy in determining the worker's level of effort. We will discuss these other sources of spillovers more

[4]Theoretical results are shown in Section A.2 in Appendix A.

[5]Section A.2 in Appendix A shows theoretical results for this case as well.

in details when presenting the evidence supporting the mechanisms and the empirical salience of alternative explanations to our findings in Section 6.

3 The Setting

Our aim is to investigate whether individual effort changes with coworkers' productivity in those contexts where workers handle inputs of heterogeneous quality, and whether human resource management practices play any role in shaping the sign and size of these spillovers. We take these questions to the data by focusing on an egg production plant in Peru. The establishment belongs to a leading poultry firm having egg production as its core business. In the plant under investigation, production takes place in several *sectors*. An aerial photograph of a given production sector is shown in Figure 1. Each sector is divided into several different long-shaped *sheds*, as pictured in the Figure. Each shed hosts one to four *production units* which constitute the ultimate unit of operations in the plant. A given shed hosting four production units is pictured in Figure 2.

Each production unit is defined by one worker and a given batch of laying hens assigned to him. Hens within a given batch are very homogeneous in their characteristics. In particular, they are all of the same age. This is because birds in the same batch are bought altogether when still eggs from an independent bird supplier company. After birth, they are raised in a dedicated sector. The entire batch is then moved to production when hens are around 20 weeks old, and discarded altogether when reaching around 80 weeks of age. The productive life of laying hens is thus approximately 60 weeks long. During that time, the batch is always assigned to the same production unit. The position of the worker is fixed over time as well. Worker's main tasks are: (i) to collect and store the eggs, (ii) to feed the hens and (iii) to maintain and clean the facilities.[6] Egg production establishments in developed countries are typically endowed with automatic feeders and automated gathering belts for egg handling and collection.[7] The production technology in the plant under investigation is thus more labor intensive relative to the frontier.

In this context, output is collected eggs. These are classified into good, dirty, broken and porous, so that measures of output quality can be derived accordingly. The

[6]The worker's typical daily schedule is reported in Table B.1 in the Online Appendix B. Figure B.1 in the same Appendix shows the distribution of the estimated worker fixed effects as derived as described at the end of Section 5. The variance of the distribution is indicative that, conditional on input quality, workers can have a substantial impact on productivity.

[7]American Egg Board, *Factors that Influence Egg Production*, http://www.aeb.org, accessed on December 27, 2013.

batch of laying hens as a whole is instead the main production input. High quality hens increase the marginal product of effort for the worker. As we show later, hens' productivity varies with age, which generates both cross-sectional and time variation in input quality across workers.

Production units are independent from each other and no complementarities nor substitutabilities arise among them. Indeed, each worker independently produces eggs as output combining effort and the hens assigned as input to him. Egg storage and manipulation (selection, cleaning, etc.) is also independent across production units. As shown in Figure 2, each production unit is endowed with an independent warehouse for egg and food storage. Nonetheless, workers in neighboring production units in the same shed are likely to interact and observe each other. In particular, the productivity of working peers can be easily monitored as they take boxes of collected eggs to the warehouse located in front of each production unit. On the contrary, workers located in different sheds can hardly interact or see each other.

Workers in the firm are paid a fixed wage every two weeks. On top of this, a bonus is awarded to the worker when his productivity on a randomly chosen day within the same two weeks exceeds a given threshold. In this case, a piece rate pay for each egg box exceeding the threshold is awarded. For simplicity, the piece rate component of pay will be ignored in the first part of the analysis. In the second part, the impact of both incentive pay and social incentives on productivity and externalities will be explored and tested.

4 Data and Descriptives

The basis for our empirical analysis is daily production data from one sector of the plant from March 11 to December 17 of 2012. The data are collected by the veterinary unit at the firm with the purpose of monitoring hens' health and productivity. Our unit of observation is one production unit as observed on each day during the sampling period. We observe a total number of 99 production units, grouped into 41 different sheds. The majority of sheds (21) is indeed composed of 2 production units. A total of 97 workers are at work in the sector for at least one day, while we can identify 186 different hen batches in production throughout the period. Batch replacement and hens' age represent the main sources of variation for identification of productivity spillovers.

For each production unit on each day, we can identify the assigned worker and the hen batch in production on that day. For each hen batch, we have information on the total number of living hens and their age in weeks on each day, together with a number of additional baseline batch quality measures as derived before the same was moved to production, such as mortality and weight distribution moments. Furthermore, we also have data on the weekly number of eggs that each hen in a given batch is expected to lay in each week of age. This information is provided by the independent bird supplier company from which laying hens were bought in the first place. Notice that such expected productivity measure is predetermined and thus exogenous to anything specific to the egg production phase, including workers' characteristics and their effort choice. In terms of output, we have precise information on the total number of collected eggs. We can thus derive a measure of worker's daily productivity as the average number of eggs per living hen collected by the worker in each production unit on each day.

Our chosen productivity measure is therefore the daily number of eggs per living hen. This is because we want to factor out differences among coworkers in input *quantity*, and focus on heterogeneity in input *quality*. In other words, we want to focus on differences across batches along dimensions other than their numerosity, since the latter would be a trivial source of variation for total output.[8] Remember that a single worker operate each production units. We thus label the worker as more productive if she collects a higher number of eggs while operating the same number of hens. This is not conceptually different from what we would say of a firm which is capable of achieving higher output levels while using the same amount of inputs. Following this definition, and consistent with the above conceptual framework, productivity is therefore in this context a function of both worker's effort and input quality, where the latter is related to hens' characteristics. We develop this point extensively in the following Section.[9]

The data also carry information on the number of good, dirty, broken and porous eggs, together with the daily number of hens dying on each day. Finally, we have information on the daily amount of food handled and distributed across the hens by the worker as measured by the number of 50kg sacks of food employed.

Summary statistics for the variables of interest are shown in Table 1. Given the focus on productivity spillovers, observations belonging to sheds hosting a single production unit are excluded from the study sample, leading to a final sample size of 21,213 observations, one per production unit and day.

The average productivity - daily number of eggs per living hens - across the whole sample is equal to 0.785. Consistent with the setting description above, hens' age varies

[8]The number of living hens on a given day may be by itself endogenous to worker's effort. We discuss this possibility in greater details in Section 5. In particular, results from Table 4 show that the fraction of hens dying on each day does not change systematically with coworkers' productivity. We thus conclude that our estimates of productivity spillovers are not sensitive to the adjustment by the number of living hens.

[9]One other option is to use total output as measure of productivity, and include the number of living hens as control in the regression specifications that we implement in our empirical analysis. Results are qualitatively the same as the ones reported here, and are available from the authors upon request.

between 19 and 86 weeks, while the average batch counts around 10,000 laying hens. There is substantial heterogeneity in the number of living hens in each production unit on each day, ranging from a minimum of 44 to a maximum of over 17,000. There are two main sources for this variation. First, hen batches are heterogeneous to begin with and already on the day they are moved to production. Second, within a given batch, a number of hens die as time goes by. Importantly, these are never replaced by new hens: only the entire hen batch is replaced as a whole when (remaining) hens are old enough. This is the reason why, at every point in time, all hens within a given batch have always the same age. Workers distribute an average daily amount of 112g of food per hen.[10] Derived output quality measures include the fraction of good, broken and dirty eggs over the total. On average, 86% of eggs produced by a production unit in a day are labeled as good, and are thus ready to go through packaging. 6% of eggs on average are instead labeled as dirty. Workers can turn a dirty egg into a good egg by cleaning it. Finally, an average fraction of 0.1% of hens in a batch die on a daily basis.

We also collected information on the spatial arrangement of production units within the sector, and their grouping into sheds. For each production unit, we can thus combine this information with the above data to derive productivity and input quality measures for neighboring production units in the same shed. This allows us to compute a measure of coworkers' average daily output and the average age of hens assigned to coworkers. Not surprisingly, coworkers' average variables share the same support of individual measures, but standard deviations are lower.

We complement production data with information belonging to an original survey we administered in March 2013 to all workers employed at the time in the sector under investigation. The purpose of the questionnaire was to elicit demographic and personal information about the workers, and the friendship and social relationship among them.[11] For this purpose, we asked the workers to list those among their coworkers who they identify as friends, who they would talk about personal issues or go to lunch with. We will say that worker i recognizes worker j as a friend if the latter appears in any of worker i's above lists. 63 of the interviewed workers were already employed in the period for which production data are available, so that relevant worker information can be merged accordingly. The corresponding figures will be investigated when addressing the role of monetary and social incentives in Section 7.

[10] This quantity is computed by dividing the number of 50kg sacks of food opened by the worker by the number of living hens on each day. Once the sack is opened, the food it contains does not need to be all distributed to the hens. This results in measurement error, and can explain why the maximum quantity of food per chicken in the data is almost 6kg.

[11] The questionnaire is available from the authors upon request.

5 Empirical Analysis of Productivity Spillovers

5.1 Preliminary Evidence and Identification Strategy

The batch of laying hens as a whole is the main production input in this context. The worker is assigned the same batch of equally aged hens from the moment they are moved to production until they are discarded. Crucially, hens' productivity varies with age. The more productive hens are the higher is the marginal product of effort. We thus regard input quality and effort as complements in production.[12] Figure 3 plots the chosen productivity measure - average daily number of eggs per hen - against hens' age in weeks. It plots the smoothed average together with a one standard deviation interval around it. Furthermore, for all given week of age, each bin in the scatterplot shows productivity values as averaged across all observations belonging to production units hosting hens of that given age. Figure 3 shows how productivity is typically low when hens are young and have been recently moved to production, but starts to increase thereafter. It reaches its peak when hens are around 40 weeks old. From that age onwards, productivity starts to decrease first slowly and then more rapidly once hens are over 70 weeks old. Hens' age thus induces meaningful variation in productivity. This is especially the case through the beginning and the end of the hens' life cycle, meaning from week 16 to week 32 and from week 75 to 86. These time intervals together account for around 40% of the overall productive life span.[13]

Hens' age exogenously shifts input quality and thus productivity as measured by daily output y_i. This source of variation can be exploited in order to identify productivity spillovers. Specifically, we start by considering the following regression specification

$$y_{igt} = \varphi + \gamma\, \bar{y}_{-igt} + \alpha\, age_{igt} + \beta\, age^2_{igt} + \sum_{s=t-3}^{t-1} \lambda_s\, food_{igs} + \varepsilon_{igt} \qquad (7)$$

where y_{igt} is the daily number of eggs per hen collected by worker i in shed g on day t. $\bar{y}_{-igt}$ captures the corresponding average value for coworkers in neighboring

[12] In order to understand this, let effort be measured as the amount of time devoted to a given task. A marginal increase in the time devoted to egg collection is more productive in terms of number of collected eggs the more productive hens are. We indirectly test for this hypothesis by estimating worker fixed effects in a subsample of our data, and including a variable with their values, a proxy for input quality and the interaction between the two as explanatory variables in a regression of individual productivity in the remaining sample. The coefficient for the interaction variable is positive and highly significant. This means that the same increase in input quality is associated with a differential productivity increase for high ability workers, thus showing evidence of complementarity between worker fixed effects and input quality. The details of such test are explained in Appendix A.3. We thank one anonymous referee for suggesting this procedure.

[13] As shown in Table 1, around 48% of the observations in the overall sample correspond to workers whose assigned hens are in the first or the fourth age distribution quartile.

production units on the same day. The variable age_{igt} is the age in weeks of hens assigned to worker i. Its square is included as well in order to capture the inverted U shape relationship between hens' age and productivity previously shown in Figure 3.[14] We also include three lags of total amount of food distributed $food_{igs}$ as controls. This is because we want to explore the relationship between the variables of interest at time t and conditional on one relevant dimension of effort exerted by the worker on previous days.[15] Finally, ε_{igt} captures idiosyncratic residual determinants of worker's productivity. Notice that, by conditioning on both own hens' age and food distributed on previous days, we aim to disclose the presence of any systematic relationship between coworkers' productivity and individual unobserved effort on day t as captured by γ.

Our goal is to identify the causal effect of peers' productivity on own output, conditional on own input quality. OLS estimates of the parameter of interest γ in the above equation are likely to be biased. The proposed specification defines productivity simultaneously for all workers, leading to the so-called reflection problem first identified by Manski (1993).[16] Furthermore, sorting of hens or workers with the same unobserved characteristics into sheds or the presence of idiosyncratic shed-level shocks may push in the same direction the productivity of peers on the same day, generating a spurious correlation between coworkers' outcomes (Manski 1993; Blume, Brock, Durlauf, and Ioannides 2011). Nonetheless, hens' age represents a powerful source of variation. Changes in the age of hens assigned to working peers induces exogenous variation in their productivity, so that any systematic relationship between the former and own outcomes can be interpreted as evidence of productivity spillovers.

Notice that, by using hens' age as a source of variation for coworkers' productivity, we do not need to rely on the assumption that the initial assignment of batches to workers is as good as random. Indeed, we cannot rule out that batches which are expected to be of a given quality are assigned to specific workers. Our identification strategy exploits instead variation in hens' age over time within a given batch, and its realized match with a given worker. Still, in order to identify a causal effect, the age of coworkers' hens needs to be as good as randomly assigned and have no effect on own

[14]In Section 5.2, we also use a kinked regression specification and week-of-age dummies in order to better fit the productivity-age profile shown in Figure 3. Parameter estimates are highly comparable across specifications. In our baseline specification, we prefer to adopt a quadratic functional form in oder to avoid the *many weak instruments* problems that would arise by using the full set of week-of-age dummies as instruments for coworkers' productivity.

[15]Results are qualitatively the same if we use lags of food per hen distributed by the worker.

[16]The suggested specification differs from the basic treatment in Manski (1993) in that it adopts a leave-out mean formulation, as the average productivity regressor is computed excluding worker i. Nonetheless, the simultaneous nature of the equation makes the reflection problem still relevant (Bramoullé, Djebbari, and Fortin 2009; De Giorgi, Pellizzari, and Redaelli 2010; Blume, Brock, Durlauf, and Ioannides 2011; Angrist 2014).

outcomes other than through changes in coworkers' productivity.

Given the assigned batches, coworkers' and own hens' age in weeks are both a function of time. We thus explore the correlation between the two variables conditional on the full set of day fixed effects. Even conditionally on the latter, own hens' age in weeks is found to be positively correlated with the corresponding average value for coworkers in neighboring production units on the same day. The corresponding correlation coefficient is equal to 0.89, significantly different from zero. This is because the management allocates batches to production units in a way to replace those in the same shed approximately at the same time. This is due to the logistics of the operation of replacing a batch of old hens with a new one of young hens.[17] It follows that hen batches in neighboring production units have approximately the same age. However, there is still residual variation to exploit. The primary source of this residual variation is that the exact day in which batch replacement occurs is not the same for all production units within a shed. Indeed, the correlation between coworkers' and own hens' age falls to zero when computed conditional on the full set of shed-week fixed effects. The *p-value* from the test of the null hypothesis of zero correlation between the two variables is equal to 0.54. In other words, daily deviations in the age of hens in each production unit from the corresponding shed-week and day averages are orthogonal to each other.[18][19] Moreover, the exact day of coworkers' batch replacement is not correlated with any pre-existing trend in individual productivity. Table B.3 shows the coefficient estimates from a regression of a dummy equal to one if the batch assigned to neighboring coworkers was replaced in a given day over lags of individual productivity

[17] The old batch is typically loaded on a truck, which then travels to the main operation center to be unloaded. Maintenance is then carried on the production unit for the next few days. When ready, the new batch is then loaded on a truck in the raising sector and taken to the production unit, where the new batch is unloaded and positioned.

[18] Table B.2 in Online Appendix B reports the estimates of the conditional correlation coefficients. Since every hen batch in the sample is neighbor of some other batch, within-group correlation estimates using the whole sample suffer from mechanical downward bias (Bayer, Ross, and Topa 2008; Guryan, Kroft, and Notowidigdo 2009; Caeyers 2014). In order to overcome this problem, we follow Bayer, Ross, and Topa (2008) and randomly select one production unit per group as defined by the shed-week interaction (g, w). Estimates are computed using the same resulting subsample.

[19] The orthogonality hypothesis can be further tested by means of the regression specification proposed by Guryan, Kroft, and Notowidigdo (2009), which in our case becomes

$$age_{igwt} = \pi_1 \, \overline{age}_{-igwt} + \pi_2 \, \overline{age}_{-igw} + \psi_{gw} + \delta_t + u_{igwt}$$

where age_{igwt} is the age in weeks of hens assigned to worker i in shed g in week w on day t. $\overline{age}_{-igwt}$ is the corresponding average value for coworkers in neighboring production units on the same day, while $\overline{age}_{-igw}$ is the average value for peers in the same shed in all days of the week. The hypothesis of daily random assignment of age of coworkers' hens within each shed-week group is equivalent to the null $H_0 : \pi_1 = 0$. Regression results are reported in the bottom panel of Table B.2 in the Online Appendix B, showing that H_0 cannot be rejected.

as measured by the daily average number of eggs per hen. Evidence shows the absence of any systematic relationship between past productivity and the probability of a batch replacement in neighboring production units.

Evidence allows us not to reject the hypothesis that, conditioning on the whole set of day δ_t and shed-week fixed effects ψ_{gw}, the age of hens assigned to coworkers is as good as randomly assigned to a given worker and his own hens' age. It follows that the age of coworkers' hens can be used as a source of exogenous variation in order to identify the causal effect of an increase in coworkers' productivity on own productivity.[20]

5.2 Baseline Results

Table 2 presents the first set of regression results. In the first column, the daily average number of eggs per hen collected by the worker is regressed over the age of hens in weeks and its square. The full set of day fixed effects are included as well. The proposed specification yields a quadratic fit of the dependent variable as a function of hens' age, which is consistent with the evidence in Figure 3.[21] Coefficient estimates are significant at the 1% level and confirm the existence of a concave relationship between hens' age and productivity. Standard errors are clustered along the two dimensions of shed and day in all specifications. Idiosyncratic residual determinants of productivity are thus allowed to be correlated both in time and space, specifically among all observations belonging to the same working day and all observations belonging to the same shed. In its quadratic specification, together with day fixed effects, hens' age explains 0.41 of the variability in the dependent variable. The same number rises to 0.43 when lags of the amount of food distributed are included in Column 2. The full set of shed-week dummies is included in Column 3. Notice that, despite its measurement in weeks, the age variable still induces meaningful variation in productivity as measured by the average number of eggs per hen collected: coefficients are almost unchanged with respect with those estimated in Column 2. The fraction of total variability explained is

[20]Several contributions in the literature exploit within-group random variation in peer characteristics in order to identify peer effects (see for instance Sacerdote 2001; Ammermueller and Pischke 2009; Guryan, Kroft, and Notowidigdo 2009). In the context of the proposed specification, the parameter γ can be correctly identified using 2SLS under the additional assumption of no effect of the age of coworkers' hens on own productivity other than through changes in coworkers' productivity, as discussed in the next section. The variation we exploit for identification is meaningful. Conditional on day fixed effects, within-shed-week variation accounts for 5.4% of the total variation in the age of coworkers' hens in the sample, measured in weeks. The same fraction goes up to 35% for observations belonging to those weeks in which any batch replacement took place in the shed. As we discuss later, we estimated separately the effect of interest for observations belonging to weeks with and without any batch replacement, finding similar results. Results are shown in Table B.6 of the Online Appendix B.

[21]As previously mentioned, in Section 5.2 we also use a kinked regression specification and hens' week-of-age dummies in order to better fit the productivity-age profile.

now up to 0.86.

In Column 4 of Table 2, we include the average age of hens assigned to coworkers in neighboring production units and its square as additional regressors.[22] The coefficients of the own hen's age variables experience almost no change in magnitude, confirming the absence of any systematic relationship between own and coworkers' hens' age within each shed-week group.[23] Any systematic relationship between the average age of coworkers' hens and own productivity can thus be interpreted as reduced-form evidence of productivity spillovers. The corresponding coefficients are highly significant and opposite in sign with respect to the ones of own hens' age.[24] This result is confirmed in Column 5 of Table 2, which also includes worker fixed effects. The latter allow to detect systematic differences in the outcome of the same worker according to differences in the average age of coworkers' hens. The corresponding R^2 is now equal to 0.89. Consistent with regression results, Figure 4 shows how, once own hens' age, day and shed-week fixed effects are controlled for, the relationship between residual productivity and the age of coworkers' hens is u-shaped: the opposite with respect to the one between productivity and own hens' age. Therefore, conditional on own hens' age, workers' productivity is systematically higher when coworkers' assigned hens are on average either young or old, and thus of low productivity. The opposite holds when the age of coworkers' assigned hens is close to the productivity peak. In other words, conditional on own input quality, workers' productivity is systematically lower (higher) when coworkers are assigned inputs of higher (lower) quality. We interpret this result as reduced-form evidence of negative productivity spillovers.

Hens' age induces meaningful variation in workers' productivity. Quasi-random variation in the average age of coworkers' hens can thus be exploited in order to identify the parameter γ from the main specification above. However, in order to do so, the age of coworkers' hens needs to have no direct effect on own outcomes. If the exclusion restriction is met, the effect of coworkers' productivity can be correctly identified by means of a 2SLS estimator.[25] In this respect, the specific features of the production environment under investigation suggest the absence of any effect of the characteristics of coworkers' hens on own productivity. In particular, the production technology is independent among production units. One possible concern is that hens may be more

[22] Caeyers (2014) shows that no mechanical downward bias arises in the estimation of the parameters of interest in this reduced form specification.

[23] The coefficients of the own hen's age variables do not change even adding coworkers' hens' age and its square separately as controls one by one, as shown in Table B.4 in the Online Appendix B.

[24] Notice that residual positive correlation between coworkers' and own hens' age would let the coefficient of the corresponding variables be of the same sign.

[25] Again, Caeyers (2014) shows that no mechanical downward bias arises in the estimation of the parameters of interest in the specification of interest using 2SLS.

prone to experience transmittable diseases as they get old, and the disease may spread to neighboring production units. However, notice that coworkers' productivity would be positively correlated in this case, while results from Table 2 already suggest the effect of interest to be negative. The true value of the parameter of interest would be even more negative than its estimate in this case.[26]

The first column in Table 3 reports OLS estimates of the parameters from the main regression specification. As mentioned before, the parameter estimate $\hat{\gamma}_{OLS}$ is likely to be biased in this case. Column 2 provides 2SLS estimates of the parameter of interest. Using both the average age of hens assigned to coworkers and its squared as instruments for coworkers' productivity, the value of the *F-statistic* of a joint test of significance of the instruments in the first stage regression is equal to 43.66. The two instruments together are thus relevant in inducing variation in the regressor of interest.More importantly, the 2SLS estimate $\hat{\gamma}_{2SLS}$ is negative and significant at the 1% level. OLS and 2SLS estimates are of very similar magnitude. One possible explanation for this result is that the different sources of bias of OLS estimate in this case work both in the positive (sorting, correlated effects) and negative direction (reflection, mechanical bias from the inclusion of group fixed effects as discussed in Guryan, Kroft, and Notowidigdo 2009 and Caeyers 2014), and they may cancel each other out. One other possibility is that the inclusion of a full set of day, shed-week and worker fixed effects already solves for the bias due to unobserved common shocks and sorting to a large extent, while the relatively high large number of observations per shed-week group makes the reflection and mechanical bias problems less salient. Estimates imply that a one standard deviation increase of average coworkers' daily output is associated with a decrease in own daily output of almost a third of its standard deviation. If all workers are assigned the same number of hens, an increase of average coworkers' daily output of 500 eggs causes the number of own collected eggs to fall by 150.

The use of hens' age and its square as predictors of daily output imposes a precise functional form to the relationship between the two variables. The parameter of interest can be identified more precisely using the full set of own and coworkers' hens week-of-age dummies respectively as regressors and instruments. Column 3 shows the 2SLS parameter estimates from this alternative regression specification, which do not change with respect to the previous ones. The *F-statistic* of a joint test of significance

[26] It is nonetheless the case that hens' age is a linear function of time and is therefore predictable by the workers. Therefore, workers may directly respond to changes in the quality of inputs assigned to coworkers, and not to the resulting changes in their observed productivity. This would not invalidate the reduced-form estimates in Table 2 and their interpretation of negative productivity spillovers, but it would affect the interpretation of the 2SLS estimates of the γ parameter. Deriving these estimates is nonetheless useful in order to pin down the exact magnitude of productivity spillovers.

of all the instrument dummies in the first stage is equal to 46.90, and the R^2 turns out to be equal to 0.92. Finally, in the last column, the full set of hen batch fixed effects is included. This allows to exploit variation in hens' age over time within each assigned batch, netting out time-invariant batch characteristics which can be correlated with productivity. The first-stage *F-statistic* is now equal to 60.12, and the 2SLS estimate of the effect of interest remains unchanged and significant at the 1% level. Overall, the evidence supports the hypothesis of negative productivity spillovers among coworkers in neighboring production units.

5.2.1 Sources of Identifying Variation

In order to correctly interpret the above results, it is important to get a clear sense of the sources of the variation that we exploit for identification. For this purpose, we first investigate whether the identifying variation comes from a specific portion of the productivity-age curve. We fit the relationship between hens' age and the average daily number of eggs per hen using a kinked regression with three kinks, as shown in Figure B.2. The values of hens' age to which the three kinks correspond is chosen in order to maximize the R^2 of the kinked regression of productivity over hens' age. We therefore estimate the parameters from the main regression specification using a 2SLS estimator where coworkers' productivity is instrumented with its predicted value as derived from kinked regression estimates. The first Column in Tables B.5 shows the corresponding 2SLS estimates, which are very similar to the previous ones. In Columns 2 to 5, we implement the same regression specification, but separately for the different subsamples as defined by the kinked regression interval the age of coworkers' hens belongs to. The 2SLS estimate of the coefficient of coworkers' productivity is insignificant in all specifications. This shows that the variation that we exploit for identification does not belong to any specific segment of the productivity-age profile, but rather from its overall shape.

With the aim to dissect further the source of variation, we then go back to use again the age of coworkers' hens and its square as predictors of coworkers' daily output, but implement the same initial 2SLS strategy over different subsamples. In particular, we want to check whether the variation we exploit for identification belongs only to those periods where the match between workers and hen batches is disrupted, or instead it belongs to periods where the match is stable. First, we investigate whether worker's productivity (conditional on own hens' age) jumps discontinuously when a batch or worker replacement occurs in a neighboring production. Figures B.3 and B.4 plot worker's residual productivity around the day of batch and worker replacement respectively, showing no significant discontinuity at that date. We then move to analyze the data more systematically in a regression framework. In Columns 1 and 2 of Table B.6 of the Online Appendix B, we split the sample according to whether the observation belongs to a production unit and week when any batch replacement was recorded in either the worker's or the coworkers' production units. Our estimates of the parameter of interest are comparable across the two subsamples, showing that the identifying variation does not belong only to those weeks in which the batch replacement happens, but also from changes in hens' age within a given batch. The reason for this is that differences in the exact day of batch replacement map into initial differences in the age of hens assigned to coworkers. But this same difference persists over time through the productive life of these hens, even if the resulting difference in productivity levels changes over time due to shape of the age-productivity profile. Therefore, it is not surprising that age variations within a given hen batch life cycle still matter for identification.

In Columns 3 and 4 of the same table, we split the sample according to whether any worker had been replaced in the shed. The identifying variation seems to come only from those observations in which no worker replacement is recorded. Finally, in Column 5, we get rid of these shocks to the matches between workers and hen batches altogether, and estimate the coefficient of coworkers' productivity only for those observations belonging to weeks and sheds where neither worker nor batch replacement took place. Results remain highly significant and almost identical to the previous ones. This shows that the identifying variation is not restricted to those periods where the match between workers and hen batches is disrupted.

Above and beyond the specific sources of variation, one may wonder whether the effect we find is plausible, meaning whether the variation in the productivity of coworkers induced by changes in their hens' age is actually detectable by a given worker. The average difference between own and coworkers' hens' age is 3.22 weeks, corresponding to an average productivity difference of 0.06 daily eggs per hen. Figure 3 suggests that the same 3-weeks difference in age can amount to large or small productivity differences, depending on the hens' stage of life. For example, the average daily number of eggs per hen is 0.06 when hens are 19 weeks old, but is more than 8 times larger at age 22, being equal to 0.50: a 0.44 productivity difference, equal to 4,400 eggs more for a batch of 10,000 hens. A similar but opposite pattern holds when productivity starts to decrease in the last stages of a hen's life. This means that even a small variation in hen's age can have a sizable and observable impact on daily output, at least when hens are far from their productivity peak age.

5.3 Feeding Effort and Output Quality

The previous results show how, conditional on own input quality, workers' productivity is systematically lower (higher) when the productivity of neighboring coworkers exogenously increases (decreases). We claim that such negative spillover effect is due to changes in the level of effort exerted by the worker. In this respect, hens' feeding represents one observable dimension of effort which is worth investigating. For this purpose, the average amount of food per hen distributed by the worker can be replaced as outcome in the main specification. 2SLS estimates of the coefficient of average coworkers' productivity are shown in the first column of Table 4. The coefficient of interest is estimated as negative, consistent with the interpretation of previous results. However, the estimated parameter is not significantly different from zero. We thus claim the effect of coworkers' productivity to work through changes in the unobservable dimensions of effort.

Beyond the negative effect on own output, the available data also allow to derive a wide range of output quality measures. The effect of average coworkers' productivity on own output quality can be investigated accordingly. 2SLS estimates are shown in Column 2 to 5 of Table 4, where again the full set of own and coworkers' hens week-of-age dummies are included as regressors and instruments respectively. The *F-statistic* of a joint test of significance of all the instrument dummies in the first stage is sufficiently high in all specifications. An increase in coworkers' average output is associated with a systematic decrease in the own fraction of good eggs over the total. The coefficient of interest is equal to -0.15 significant at the 1% level. A one standard deviation increase in coworkers' productivity causes a 3 percentage points decrease in the own fraction of good eggs over the total. The estimated coefficient of interest is instead positive when the own fraction of broken eggs over the total is investigated as outcome in Column 3, even if not statistically significant. An increase in average coworkers' productivity is instead found to significantly increase the own fraction of dirty eggs over the total. Indeed, the estimated coefficient in Column 4 is significant at the 5% level and equal to 0.07: a one standard deviation increase in average coworkers' output is associated with a 1.32 percentage point increase in the own fraction of dirty eggs over the total. Recall that workers can turn a dirty egg into a good egg by cleaning it. This result therefore indicates that workers exert less effort in cleaning dirty eggs when coworkers are more productive. Finally, the fraction of hens dying in the day is considered as outcome in Column 5. The estimated coefficient of interest is negative, but not statistically different from zero. This is particularly important, as the number of living hens on a given day may be by itself endogenous to worker's effort. The absence of a systematic relationship between hens' death and coworkers' productivity let us conclude that our estimates of productivity spillovers are not the result of a strategic decision of workers to adjust the number of living hens to coworkers' input quality. Overall, estimates in Table 4 show that coworkers' productivity negatively affects not only own output but its quality as well.

These results altogether suggest that coworkers' productivity does not affect all the dimensions of worker's effort in the same way. When looking at the amount of food distributed, the coefficient of coworkers' productivity is negative but imprecisely estimated. The effect of coworkers' productivity on own productivity seems thus to work through changes along other dimensions of effort, such as the way the same amount of food is distributed across the hens. Egg cleaning effort is also negatively affected, while coworkers' productivity does not seem to affect those components of effort which map into hens' survival probabilities, such as cleaning and maintenance of the facilities. These results can be explained by the level of heterogeneity in the observability of each one of these different effort categories, which in turn determine the scope for free riding. Indeed, while it is easier for a worker to detect if a coworker is shirking on the amount of food distributed to the hens or the maintenance of facilities, it is supposedly harder to detect the effort exerted by coworkers in smoothing the same amount of food across the hens.

5.4 Robustness Checks and Effect Heterogeneity

Workers in non-neighboring production units can hardly interact or observe each other. We exploit this feature of the production environment to further validate the previous results by means of a *placebo test*. First, the average number of eggs per hen collected by workers in the adjacent shed can be replaced as regressor in the main specification, and age of their hens can be again used as a source of exogenous variation for their productivity. Column 1 of Table 5 reports the 2SLS estimate of the corresponding coefficient using as instrument the full set of coworkers' hens week-of-age dummies. In this case, coworkers' variables are the same for all workers in a shed, so no daily within-shed variation is exploited. Therefore, the strength of the first stage relationship is lower than in the main specification, but the corresponding *F-statistic* of a joint test of significance of the instruments is still high and equal to 11.01. As expected, the resulting 2SLS point estimate is negligible in magnitude and not significantly different from zero. The same holds when restricting the sample to workers located in sheds with more than two production units, and considering as main regressor the average number of eggs per hen collected by workers in non-neighboring production units in the same shed. Results are reported in Column 2. Taken together, we interpret these findings as evidence that observability between workers plays a crucial role for the effect we find.[27]

Furthermore, the natural logarithm of the daily average number of eggs per hen collected can be replaced as outcome in the main specification.[28] Adopting the same identification strategy, as shown in Column 3 of Table 5, the coefficient of coworkers' productivity is found to still be significant at the 1% level and equal to -1.47. In other words, an increase in coworkers' average output of one standard deviation is associated with a 29% decrease in own output.

Finally, in Column 4 of Table 5, we implement an alternative identification strategy where the expected hens' productivity is used as instrument for coworkers' average result. Such expected productivity measure is elaborated by an independent bird supplier company, which sells the animals to the firm under analysis. The variable is thus exogenous to anything peculiar of the firm and its production process. The measure gives the average number of eggs per week each hen is expected to produced at every week of its age. We divided it by 7 in order to derive the expected daily productivity. In the causal framework under investigation, expected productivity can be readily interpreted as the *assignment-to-treatment* variable, with the *treatment* being actual coworkers' productivity. The first-stage *F-statistic* turns out to be equal to 29.56. The estimated parameter of interest is highly significant and remarkably similar to the ones derived before.[29]

The average result of negative productivity spillovers can be further explored along one specific dimension of heterogeneity: workers' ability. Similarly to Bandiera, Barankay, and Rasul (2005) and Mas and Moretti (2009), we estimate the full set of worker fixed effects in a regression specification where hens' week-of-age dummies, batch and day fixed effects are also included as regressors.[30] We then split the workers into *high* and *low* ability according to their position relative to the median in the estimated fixed effects distribution, and assign observations belonging to the worker's assigned production unit to two corresponding subsamples. The parameter of interest is estimated

[27] We find the same results when using the age of own and coworkers' hens and their square as controls and instruments respectively as in the first proposed specification.

[28] Such transformation is needed in order to match the conceptual framework proposed in Section 6. Indeed, if effort e_i and input quality s_i are complements and $y_i = e_i s_i$, then $\ln y_i = \ln e_i + \ln s_i$. Variable values are augmented by 0.01 before taking the log. Implementing a log-log specification we can estimate the elasticity of own productivity with respect to coworkers' productivity, equal to 0.35, with the estimate being significant at the 1% level.

[29] We also perform two additional robustness checks. First, we address the identification concerns in Angrist (2014) by explicitly separating the subjects who are object of the study from their peers. Specifically, we randomly select one production unit per each shed-week and run the main identifying regression over the restricted sample only. Second, we drop out all observations belonging to those days in which the worker assigned to a given production unit was listed as absent. Results are in line with previous estimates in both cases, as shown in Table B.6 in the Online Appendix B.

[30] The distribution of workers' ability is shown in Figure B.1 in the Online Appendix B.

separately and results reported in Columns 5 and 6 of Table 5. The estimated coefficient is negative and significant only for low ability workers. High ability workers do not seem instead to be responsive to changes in coworkers' productivity. One explanation for this result is that high ability workers are more likely to hit the bonus threshold and thus be exposed to piece rate incentives. We will investigate this issue specifically in Section 7.

6 The Mechanism

Results from the previous section provide evidence of negative productivity spillovers. The productivity of coworkers in neighboring production units is found to negatively affect individual daily output and its quality. Our claim is that, while triggered by input heterogeneity, the source of externalities in this context lies in human resource management. A close inspection of the data reveals that turnover is exceptionally high at the firm under investigation. Indeed, throughout the 9 months of observations in our sample, we observe 23 terminations of employment relationship over a workforce of 97 workers. The firm we are studying is close to have monopsony power in the local labor market. Indeed, it is located in rural Peru, it pays over the sampling period an average wage which is more than 50% higher than the legally established minimum wage in the country, and close to the nationwide average wage in the period.[31] The firm is the biggest employer in the three closest small towns. Although the data we have do not allow us to distinguish between dismissals and voluntary quits, evidence is in favor of an efficiency wage argument, where the firm strategically combines high wages with high dismissal rates as disciplinary devices (Shapiro and Stiglitz 1984).

6.1 Termination Policy: Empirics

In light of the conceptual framework presented in Section 2, the evidence of negative productivity spillovers we previously found is consistent with the hypothesis that a positive shift in coworkers' productivity decreases the marginal benefits from own effort in terms of increased probability of keeping the job.[32]

We investigate this issue further through implementing a logistic hazard model and studying the relative odds of the probability $1 - q(\cdot)$ of losing the job in period t as

[31] See Section 7 and Table B.9 in the Online Appendix B for more detailed information on the wage schedule of workers at the firm. Average and minimum wage data are from the World Bank.

[32] Notice that, in our conceptual framework, an increase in input quality s_i increases productivity y_i if and only if the elasticity of effort with respect to input quality is sufficiently low in absolute value, meaning $\eta_{es} = \frac{\partial e_i}{\partial s_i}\frac{s_i}{e_i} > -1$.

defined by

$$\frac{1-q(t)}{q(t)} = \frac{h(t)}{1-h(t)} = \exp\{\, \gamma_t + \alpha\, y_{it} + \beta\, \bar{y}_{-it} + \kappa\, y_{it} \times \bar{y}_{-it} \,\} \tag{8}$$

where, y_{it} is daily average number of eggs per hen collected by worker i at time t or, alternatively, its *moving average* in period $[t-\tau, t]$, while $\bar{y}_{-it}$ is average output of coworkers in neighboring production units in the same period. γ_t captures the baseline hazard function. The interaction term aims to disclose any systematic relationship between changes in coworkers' productivity and marginal returns from own effort. In particular, the latter would decrease with coworkers' daily output if $\alpha < 0$ and $\kappa > 0$.

Maximum likelihood estimated coefficients are reported in Table 6. Two alternative definitions of baseline hazard are specified across columns. Daily productivity measures are considered as regressors in Columns 1 to 3, while 7-days moving averages are used in Columns 4 to 6.[33] Furthermore, in Columns 3 and 6 we again rely on the age of coworkers' hens as an exogenous source of variation for their productivity. Given the non-linear nature of the second stage, we follow Terza, Basu, and Rathouz (2008) and adopt a two-stage residual inclusion (2SRI) approach. As before, we use the age of coworkers' hens $\overline{age}_{-it}$ and its square as instruments for coworkers' productivity $\bar{y}_{-it}$, and their interaction with own productivity as instruments for $y_{it} \times \bar{y}_{-it}$. Identification of the effect of coworkers' productivity on termination probabilities is here achieved through exploiting the variability induced by the age of coworkers' hens, consistent with the previous analysis.

Table 6 shows that an increase in own productivity is significantly associated with a decrease in the odds of the probability of employment termination. Conditionally on own productivity, an increase in coworkers' productivity is also significantly associated with the a decrease in the odds of termination, with the point estimate being lower in magnitude with respect to the former. Returns from own productivity in terms of the probability of keeping the job are thus lower at the margin when coworkers' productivity increase, consistent with the proposed conceptual framework and evidence of negative productivity spillovers.

[33] We also estimated the same specification using different time windows τ for computing the productivity moving averages, keeping the function γ_t the same. Coefficient signs are found to be stable across specification. In order to evaluate the goodness-of-fit across specifications with different choice of τ, we calculated a modified *pseudo* R^2, equal to $1 - \frac{\ln L_{UR}}{\ln L_R}$, where L_{UR} is the likelihood of the estimated logistic model with all regressors, while L_R is the likelihood of the model where only γ_t is included as explanatory variable. The proposed measure of goodness-of-fit is found to decrease monotonically with τ. Furthermore, we estimated the same specification after collapsing data by pay period. Results are qualitatively similar to previous ones. The same holds if we estimate a linear probability model. Additional results are available upon request.

The adoption of such a policy on behalf of the management can be explained by the impossibility for the latter to completely net out inputs' contribution to output and perfectly infer worker's effort. In this case, coworkers' productivity conveys relevant information about the workers' effort distribution. We provide a specific example of this kind in Appendix A, where we present a modified version of the conceptual framework in Mas and Moretti (2009). We describe the learning process of the principal, who computes the expected workers' effort choice on the basis of available information on both output levels and observable input characteristics. This leads her to attach a positive weight to the average of productivity signals.

The same is true if all information about individual productivity and input quality is sufficiently costly to process.[34] Limited managerial attention can then lead managers to use shed-level productivity as a sufficient statistic in the evaluation of workers' performance, and process individual information only if the value of the former statistics is low enough (Kahneman 1973; Gifford 1998; Hirshleifer and Teoh 2003). As a result, the more productive coworkers are, the less likely is the shed to be targeted by the management for termination measures. Therefore, positive teamwork-type externalities arise in the probability of keeping the job, leading to free riding among workers. The empirical specification in equation 8 can be interpreted as the reduced-form equivalent of a firing rule of this kind.

6.2 Additional Evidence and Alternative Explanations

Our interpretation of results finds additional support in the results from a number of indirect empirical tests. First, even if the management used the total number of eggs as performance metric rather than the number of eggs per hen, the above results would not be affected. Indeed, the relationship between output and own probability of keeping the job has the same sign and is still significant if we use own total number of eggs, coworkers' average total number of eggs and their interactions as regressors in specification 8. Table B.7 in the Online Appendix B reports the corresponding coefficient estimates, ordered as in Table 6. More directly, an increase in total shed-level output is associated with a significant decrease in the probability of termination, as shown in the first Column of Table B.8 in the Online Appendix B. This holds true even if splitting the sample according to the number of production units per shed.[35]

The evidence presented above is nonetheless consistent with alternative hypotheses on the mechanism at play. One first concern is that workers may get discouraged

[34]Notice that the data we use in our analysis of productivity spillovers are collected by the veterinary unit and they are not processed by the human resource management department.

[35]Results from these additional specifications are available from the authors upon request.

and quit the job when their productivity is lower than the one of neighboring peers. However, our results show that, conditionally on total shed-level output, the difference between own and coworkers' productivity or total output is not systematically related with termination probabilities, not even differentially so across sheds with different levels of total output. Table B.8 in the Online Appendix B reports the parameter estimates from all these additional specifications. These results allow us to rule out that voluntary quits from discouragement are driving the empirical regularities described above.

Another concern is related to monitoring of workers. Suppose that workers are monitored on the job by the management, and that such monitoring efforts are limited, and targeted disproportionally more towards workers whose hens are highly productive. The negative causal effect of an increase in coworkers' productivity on own productivity could then be attributed to a higher level of shirking which follows a reallocation of monitoring efforts towards highly productive coworkers. However, if this was the case, a negative effect would also have been found when using as explanatory variable the average productivity of coworkers in non-neighboring production units in the same shed. Results from the placebo exercise in Column 2 of Table 5 in Section 5 show that this is not the case.

Even in absence of monitoring, one could imagine that workers can steal eggs from each other. If this was the case, though, we should expect an increase in coworkers' input quality to increase own productivity, as stealing opportunities would increase with coworkers' productivity. More in general, this is what we would expect if other possible sources of positive productivity spillovers are present, such as knowledge spillovers from social learning whose scope increases when hens are highly productive. All these explanations would bias our baseline results in the opposite direction with respect to what we find. Therefore, if these are present, our estimate of negative spillovers is only a lower bound (in magnitude) for the true effect.

A more pressing issue is whether the negative effect we find is the result of some cooperative strategy workers are playing. We explore this possibility more in details when discussing the empirical evidence on social incentives in the following Section.

7 Evidence on Monetary and Social Incentives

The setting under investigation carries with it sufficient variation in both the payment schedule and the social relationships among coworkers. In the period under consideration, workers are paid every two weeks. Their wage corresponds to the sum of a base salary plus a variable amount. The latter is conditional on and linear in the number of boxes of eggs collected by the worker in a randomly chosen day within the two weeks.

Specifically, wage is calculated according to the following formula

$$w_i = \omega \; + \; \delta \; + \; \max \{ \, 0 \, , \; \gamma \times [\, 2Y_i - r \,] \, \} \tag{9}$$

where ω is the base pay and Y_i is the amount of boxes of eggs collected by the worker in the randomly chosen day. This quantity is multiplied by 2 and, if the resulting quantity exceeds a given threshold r, a piece rate pay γ is awarded for each unit above the threshold. On top of base pay, almost all workers are awarded an extra amount δ. The bonus component is on average equal to 15% of the base pay. Average total pay in the two-weeks period is equal to the equivalent of 220 USD.[36]

As shown before, a strong relationship exists between the age of hens assigned to a worker and his productivity. Notice that no component of worker's pay is adjusted by the age of hens the worker is assigned in the pay period. As a result, the probability for the worker of earning extra pay also depends on hens' age. Figure 5 plots the distribution of the average number of daily egg boxes collected by the worker within each pay period per quartiles of the hens' age distribution. For each quartile, the boundaries of each box indicate the 10th and 90th percentile of the egg boxes distribution, while the horizontal lines within each box correspond to the mean. The ends of the vertical lines indicate the 1st and 99th percentile. The straight horizontal line corresponds to the normalized bonus threshold $r/2$. First, notice that the inverted U shape relationship between hens' age and productivity can be still observed when considering egg boxes as a measure of productivity. Second, the probability of reaching the threshold and be exposed to incentive pay is higher for those workers whose hens are of high productivity, meaning they belong to the second and third quartiles of the hens' age distribution. On the contrary, the average worker whose hens belong to the first or fourth quartile of the hens' age distribution does not reach the bonus threshold.[37]

In order to provide suggestive evidence on the role of monetary and social incen-

[36] Table B.9 in the Online Appendix B shows the corresponding summary statistics for the base pay, the bonus component and total pay. Average base pay (ω) is equal to 505 PEN (Peruvian Nuevo Sol), equal to around 190 USD. The average of the bonus component of pay ($\delta + \max\{0, \gamma \times [\, 2Y_i - r\,]\}$) is instead equal to 82 PEN, around 30 USD (δ=40 PEN).

[37] Table B.10 in the Online Appendix B shows the average base pay, bonus pay and total pay for the average worker across the assigned hens' age distribution, confirming the existence of a strong relationship between hens' age and bonus pay. Notice that small variations in base pay are observed across productivity categories. Base pay can indeed still vary with workers' age, tenure and base contract. Nonetheless, most of the variation in total pay is due to variations in the bonus pay component.

tives, we explore effect heterogeneity through the following regression specification

$$\begin{aligned} y_{igwt} &= \varphi_{gw} + \textstyle\sum_d \psi_d \, D_{digwt} \\ &+ \textstyle\sum_d \left\{ \gamma_d \, \bar{y}_{-igwt} \;+\; \alpha_d \, age_{igwt} \;+\; \beta_d \, age^2_{igwt} \right\} \times \; D_{digwt} \\ &+ \textstyle\sum_{s=t-3}^{t-1} \lambda_s \, food_{igsw} \;+\; \mu_{igwt} \end{aligned} \tag{10}$$

where φ_{gw} are the shed-week fixed effect and D_d are dummy variables which identify the heterogeneous categories of interest. The same dummy is interacted with both own hens' age variables and coworkers' productivity. With the additional inclusion of worker fixed effects, this specification allows to exploit within-worker variation and separately estimate the effect of coworkers' productivity for the same worker across heterogeneous categories. In order to solve for the endogeneity of the variable of interest, both $\overline{age}_{-i}$ and $\overline{age}^2_{-i}$ are multiplied by D_d, and the resulting variables are used as instruments for the endogenous interaction variables $\bar{y}_{-igwt} \times D_d$.[38]

We first focus on monetary incentives. As shown in Figure 5, workers whose assigned hens are either young or old are less likely to make it to the productivity threshold and thus to be exposed to piece rate pay. We thus define a first *low productivity age* subsample of production units whose hens' age is in the first or the fourth age distribution quartile, and group the rest of observations in a second *high productivity age* subsample. As shown in Table 1, 52% of the observations in the overall sample correspond to workers whose assigned hens are in the first or the fourth age distribution quartile. Column 1 of Table 7 provides the corresponding 2SLS estimates from the above specification, with D_d identifying the two resulting subsamples. The Table reports the *F-statistic* from the Angrist-Pischke multivariate F test of excluded instruments (Angrist and Pischke 2009), which confirms the first stage relationship to be strong enough. Consistent with the modified conceptual framework, no significant effect of coworkers' productivity on own productivity is found when the worker is assigned highly productive hens. The effect is instead negative and highly significant for the same worker when assigned hens are less productive and the piece rate threshold is less likely to be achieved. However, since most of the variation in productivity belongs to this region, the result can only be interpreted as suggestive evidence on the role of monetary incentives.

[38] We also estimate the main regression specification using 2SLS separately for each subsample as identified by the dummy D_d. Results are available from the authors upon request. Even if still consistent with the extended model's prediction, they are somewhat weaker with respect to what we find by implementing the proposed specification with interaction variables. The difference can be explained by the fact that the latter constrains the fixed effects estimates and coefficients of food variables to be the same across categories.

In order to explore the role of social incentives, we rely instead on the information about the friendship network among coworkers as elicited through the questionnaire we administered in March 2013. Linking the relevant information with productivity data, we identify those workers working along someone they recognize as a friend. We thus define two separate categories accordingly and let dummy variables D_d identify the corresponding subsamples. We then implement the above regression specification and get two separate estimates of the effect of coworkers' productivity, according to workers' friendship status. As reported in Table 1, 25% of the observations in the overall sample correspond to workers we interview in March 2013 who recognize at least one of their coworkers in neighboring production units as their personal friend. 2SLS estimates are reported in Column 2 of Table 7.[39] Productivity spillovers are estimated to be negative and significant only for those workers who do not work along friends. Consistent with the peer pressure argument outlined before, a positive point estimate is instead found for the coefficient of coworkers' productivity when the worker recognizes any of his coworkers as a friend, even if the 2SLS estimate is not statistically significant.

Perhaps more importantly, this last result allows to rule out the possibility that the negative effect we find is the result of some cooperative behavior workers are engaged in. For instance, workers whose hens are at their age productivity peak could benefit from the help of neighboring coworkers, with negative productivity spillovers on the latter. Such cooperative strategy would be sustainable in a repeated interaction framework. In particular, we expect such strategy to be even more sustainable among friends, due to the supposedly higher costs of deviation from the cooperation path. The absence of any significant effect in this case speaks against this hypothesis.[40]

Questionnaire data can further be explored to study effect heterogeneity according to workers' experience. We again implement the same specification as above, but define the two dummies D_d as capturing whether the worker's experience in the firm is above or below the median. 52% of observations in the overall sample to belong to workers with on-the-job experience above the median, as shown in Table 1. Estimation results are shown in Column 3 of Table 7. Negative highly significant estimates of the coefficient of coworkers' productivity are found for more experienced workers, while the same estimated parameter is positive but non-significant for less experienced workers. Results can be interpreted in light of the termination policy mechanism originating neg-

[39] Notice that the number of observation is reduced. This is because we are forced to restrict the sample to only those observations which we can merge with workers' information elicited in March 2013.

[40] Notice that allowing the friendship relationship measure as elicited in March 2013 to be endogenous to the implementation of cooperative strategies makes this point even stronger. Indeed, we should find even more of a negative effect of coworkers' productivity in this case for those workers who are working along friends.

ative productivity spillovers. Indeed, it is reasonable to think of experienced workers as having learned over time and thus being more aware of management policies. It is thus not surprising to find that the effect arises in this category.[41]

Finally, we investigate the effect heterogeneity according to the difference (in absolute value) between the age of own and coworkers' hens. In particular, we now define the two dummies D_d depending on whether such difference is higher or lower than the mean difference in the sample, equal to 3.22 weeks. We estimate the corresponding equation with 2SLS for the *low productivity age* and the *high productivity age* subsamples separately, where the latter are defined as in Column 1. If the free riding mechanism in the absence of piece rate incentives is responsible for the average effect we find, we should expect the negative effect of coworkers' productivity to be the highest in magnitude when the scope of free riding is the widest. This corresponds to the situation in which a given worker is assigned lowly productive hens while coworkers are assigned highly productive ones. The size of the effect should then be lower when both workers are assigned lowly productive hens. The same magnitude should be even lower when both workers are assigned highly productive hens, and the lowest when the worker is assigned highly productive hens and his coworkers are assigned lowly productive ones. Evidence from Column 5 and 6 is supportive of this hypothesis. The effect is only statistically significant when workers' hens are lowly productive (i.e., drawn from the first or fourth quartile of the hens' age distribution) and the absolute difference in age with coworkers' hens is high, meaning coworkers' hens are more likely to be in their high productivity age. Point estimates are ordered as suggested above, even if none of the three other 2SLS estimates is statistically significant.

8 Counterfactual Policy Analysis

8.1 Termination Policy

The evidence gathered so far suggests that the worker evaluation and termination policy implemented at the firm generates negative productivity spillovers among coworkers. In order to shed light on the salience of this issue and its consequences on aggregate productivity, we now aim to evaluate counterfactual productivity outcomes under al-

[41] Further exploring effect heterogeneity, we can estimate the parameters of this same regression specification separately for those observations belonging to workers working along more and less experienced coworkers respectively. The negative effect of coworkers' productivity is the biggest in magnitude for experienced workers working along experienced coworkers. This allows to rule out the possibility that the result in Column 3 of Table 7 is driven by experienced workers helping less experienced neighboring coworkers. Additional results are available upon request.

ternative termination policies implementable by the management. In other words, our objective is to estimate workers' average productivity under different specifications of the $q(\cdot)$ function.

In order to do this, we start from the first order condition which defines the worker's exerted effort and structurally estimate the unobserved parameters of the equation. We then simulate daily productivity y_{it} for all workers under a new alternative policy $\tilde{q}(\cdot)$.[42] In particular, we are interested in the productivity effect of shutting down the externalities among coworkers generated by and built in the current policy. It is thus reasonable to evaluate productivity counterfactuals under a policy of the form

$$\tilde{q}(y_{it}) = \alpha_0 + \alpha_1\, y_{it} + \alpha_2\, y_{it}^2 \tag{11}$$

with $\tilde{q}_1(\cdot) > 0$ and $\tilde{q}_{11}(\cdot) \leq 0$.

Table 8 shows counterfactual productivity gains and losses as predicted under the alternative termination policy. For each parameter values, each entry shows the simulated percentage change in productivity as measured by average daily number of eggs per hen collected by the worker over the period. The table also reports 95% confidence intervals as computed by repeating the above estimation procedure 100 times using bootstrapped samples. As the the coefficient α_1 in the alternative termination policy function gets high enough, productivity gains are remarkably stable and as high as 20%.

8.2 Input Allocation

While the source of externalities lies in human resource management practices, evidence shows how these are triggered by the heterogeneity in inputs assigned to neighboring coworkers. Therefore, we expect the way inputs are allocated among workers to affect overall productivity. Notice that, in our basic regression specification, coworkers' productivity enters linearly in the equation defining worker's productivity. As a result, in this framework, the effect of input reallocation on overall productivity will only operate through pairwise exchanges between production units both within and across sheds of different size. In order to understand this, think about the extreme case of a given number of sheds each hosting two production units. In this specific case, input reallocation would not affect the total amount of externalities and aggregate productivity would not be affected.[43] If instead some sheds host one or more than two production units, input reallocation within and between sheds will affect the total amount of externalities

[42] We describe the full procedure to derive counterfactual productivity estimates in Appendix A.4.

[43] Graham (2011) provides a formal discussion of this result.

generated in the system. Aggregate productivity will respond accordingly.

The impact of input allocation in our setting can be evaluated by means of a counterfactual simulation exercise. We first implement a fully specified reduced-form regression model where the daily average number of eggs per hen y_{it} is regressed over the full sets of own and coworkers' hens' week-of-age dummies, together with shed-week fixed effects. Starting with the hen batches in production in the first week of the sample and keeping their allocation fixed, we then simulate their age profiles over the sampling period, assuming hens were replaced after the 86th week of life. Using parameter estimates from the previously specified regression specification, we then predict the daily productivity of workers in each production unit. The dash-dot red line in Figure 6 shows the smoothed average of daily productivity as predicted following the procedure described above. The continuous blue line is instead the smoothed average of actual daily productivity. The two curves match closely, except for some weeks in the second half of the sampling period, when, according to the management, some sheds were affected by bird disease.

The same parameter estimates used to predict daily productivity of workers under the actual input allocation can be used to predict productivity under alternative input allocations. For example, taking the batches in production in the first week of the sample, it is possible to reallocate them among production units following a *hierarchical clustering* procedure which minimizes the variance of the age of hens within the same shed, which seems to be the goal the management tries to achieve. We simulate hens' age profiles over the period under the alternative allocation (assuming the same replacement policy as before), and predict worker's daily productivity using the same parameter estimates derived at the beginning. The smoothed average of estimated productivity is depicted by the dashed green line in Figure 6. Productivity gains are substantial, up to 20% in a given day, even though counterfactual productivity values are also more volatile than actual ones. When averaged throughout the period, the difference between the counterfactual and actual productivity is equal to 0.08, which corresponds to a 10% increase.

Counterfactual productivity can be also estimated under alternative scenarios. In particular, the same batches in production in the first week of the sample can be randomly allocated to production units. Simulated hens' age profiles and predicted worker's daily productivity can be derived accordingly with the same procedure described above. We calculate counterfactual productivity under 100 alternative scenarios of this kind, where hen batches are randomly allocated to production units. The average productivity difference throughout the sample period between the actual and the counterfactual productivity is always positive, with the average being equal to 0.0195 and significantly different from zero.[44] Results confirm that, helding everything else constant, lowering the variance of the age of hens within the same shed has a positive impact on average productivity. By comparing the actual allocation of batches to a random one, we can see how the firm has already gone a long way towards internalizing this.

8.3 Discussion

Results from the counterfactual policy analyses suggest that productivity would be up to 20% higher if the firm implemented either of the two policies under consideration, meaning revise their termination policy or fully segregate batches into sheds according to hens' age. A natural question is therefore why the firm has not implemented these changes already. In Section 6.1, we already discussed how the implementation of the termination policy in place at the firm can be rationalized in a model which factors in the cost of processing information on individual productivity levels and input quality on a daily basis. Even if these were lower than the increase in revenues following the productivity increase resulting from the implementation of the alternative termination policy discussed in Section 8.1, managers lacked precise estimates of the magnitude of negative spillovers. Therefore, they had incorrect information on the cost-benefit calculation. This is not surprising in the context of a large firm operating in a developing country. Bloom, Eifert, Mahajan, McKenzie, and Roberts (2013) make the same argument to justify the lack of adoption of productivity and profit-enhancing management practices in their study of large Indian textile firms.

As for the implementation of a fully segregated allocation of input batches according to hens' age, notice first that in the last paragraph of Section 8.2 we show how actual productivity levels are higher than the ones we predict in case batches were randomly allocated to production units. The management has therefore gone a long way already in implementing an allocation of batches into sheds which lowers the difference in hens' age across neighboring production units. Still, our results show that there is room for improvement. Having the same set of batches in production, within-shed variance in hens' age can be made even lower and minimized by reallocating them. Perhaps more importantly, the cost of reallocation only needs to be paid once, as co-movements in hens' age over time will ensure that the latter keeps being synchronized among neighboring production units. However, this also means that, once hens get old enough and need to be discarded, all batches belonging to production units within a given shed need to be substituted simultaneously. This is simply not feasible using the current technol-

[44] Figure B.5 in the Online Appendix B shows the distribution of the average productivity difference across the 100 alternative scenarios.

ogy for batch replacement.[45] Therefore, the fully segregated allocation of input batches according to hens' batches is not possible to be maintained over time, unless the firm decides to invest in a new and more efficient batch replacement technology. The cost of this investment may offset the net present value of increased revenues resulting from higher productivity. Finally, we showed in Section 8.2 how the predicted counterfactual productivity under a fully segregated allocation of input batches was more volatile as compared to the actual one. To the extent to which volatility in production enters negatively the objective function of the firm, the management at this firm won't implement such alternative allocation of inputs, despite its positive impact on average productivity.

9 Conclusion

Production and human resource management practices interact and generate externalities among coworkers in their choice of productive effort. When workers produce output using both effort and inputs of heterogeneous quality, and workforce management brings about externalities among workers, input allocation determines the total amount of externalities in the system, and matters for aggregate productivity. In the specific case of worker evaluation and dismissal policies, if these generate teamwork-type externalities, input allocation triggers free riding and negative productivity spillovers among neighboring working peers.

We exploit quasi-random variation in the productivity of workers' assigned inputs in order to identify and measure the effect of an increase of coworkers' productivity on own output and its quality. We find evidence of negative productivity spillovers. A one standard deviation increase in coworkers' average daily output causes a given worker's output to drop by almost a third of a standard deviation. We also find negative and equally sizable effects on output quality. This evidence is contrasted with the results from the analysis of workforce turnover data, which validate the specific mechanism identified by theory. A given worker's probability of keeping the job is positively associated with both own and coworkers' productivity, with the latter diminishing marginal returns own productivity. Workers thus free ride on each other and lower their effort supply when coworkers' productivity increases. In the second part of the paper, we also provide suggestive evidence that both monetary and social incentive provision can mitigate the workers' tendency to free ride on each other and offset negative productivity spillovers. Indeed, we find no effect of coworkers' productivity when workers are exposed to piece rate pay or work along friends. Finally, counterfactual policy anal-

[45] This is indeed where the residual variation in hens' age we exploit for identification in the empirical analysis comes from.

ysis derived from structural estimations reveal the impact of both input allocation and dismissal policy to bring about up to 20% average productivity gains.

This paper shows that the analysis of relatively more complex production environments may uncover the interaction between different aspects of human resource and production management. We here focus on the externalities generated by the worker termination policy, and the resulting productivity spillovers from heterogeneous inputs. Yet, inputs can also trigger productivity spillovers of alternative origins. In a companion paper still work in progress, we investigate both theoretically and empirically how workers influence each other in their choice of inputs while updating information on the productivity of the latter from own and coworkers' experience.

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Tables and Figures

TABLE 1: SUMMARY STATISTICS

Variable	Obs.	Mean	St. Dev.	Min	Max
Daily Eggs per Hen, y_i	21,213	0.785	0.2	0	1
Hens' Age (weeks)	21,213	45.327	17.016	19	86
No. of Hens	21,213	9,947.792	3,869.995	44	17,559
Food (50kg sacks)	21,213	22.351	8.936	0	40
Food per Chicken (g)	21,213	112.029	50.154	0	5,947.137
Good/Total	21,044	0.857	0.093	0	1
Broken/Total	21,044	0.024	0.037	0	0.357
Dirty/Total	21,044	0.059	0.048	0	1
Porous/Total	21,044	0.052	0.058	0	1
Deaths/No. of Hens	19,623	0.001	0.017	0	0.782
Daily Eggs per Hen Coworkers' Average, $\bar{y}_{-i}$	21,213	0.784	0.197	0	0.999
Hens' Age Coworkers' Average (weeks)	21,213	45.248	16.604	19	86
Dummies:					
Low Productivity Hens' Age	21,213	0.520	0.499	0	1
Working Along Friend	16,595	0.246	0.431	0	1
Experience Above Median	16,595	0.515	0.5	0	1

Notes. The table reports the summary statistics for all the variables used throughout the empirical analysis. The unit of observation is the production unit in the sector under investigation in each day from March 11 to December 17 of 2012. Sheds hosting only one production units are excluded from the sample.

TABLE 2: OWN AND COWORKERS' HENS' AGE AND PRODUCTIVITY

	Daily Number of Eggs per Hen, y_i				
	(1)	(2)	(3)	(4)	(5)
age_i	0.04073***	0.03903***	0.03860***	0.03805***	0.03233***
	(0.0024)	(0.0022)	(0.0059)	(0.0058)	(0.0058)
age_i^2	-0.00040***	-0.00038***	-0.00038***	-0.00038***	-0.00032***
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
$\overline{age}_{-i}$				-0.00385***	-0.00644***
				(0.0013)	(0.0024)
$\overline{age}^2_{-i}$				0.00003**	0.00005*
				(0.0000)	(0.0000)
$food_{t-1}$		0.00197**	0.00137***	0.00140***	0.00458***
		(0.0009)	(0.0005)	(0.0004)	(0.0012)
$food_{t-2}$		0.00088*	0.00078**	0.00080***	0.00300***
		(0.0005)	(0.0003)	(0.0003)	(0.0011)
$food_{t-3}$		0.00063	-0.00001	-0.00002	0.00316**
		(0.0010)	(0.0004)	(0.0004)	(0.0012)
Day FEs	Y	Y	Y	Y	Y
Shed-Week FEs	N	N	Y	Y	Y
Worker FEs	N	N	N	N	Y
Observations	21213	21213	21206	21206	21206
R^2	0.409	0.431	0.859	0.860	0.886

Notes. (* p-value$<$0.1; ** p-value$<$0.05; *** p-value$<$0.01) Ordinary Least Square estimates. Sample is restricted to all production units in sheds with at least one other production unit. Two-way clustered standard errors, with residuals grouped along both shed and day. Dependent variable is the average number of eggs per hen collected by the worker. age_i is own hens' age in weeks, while $\overline{age}_{-i}$ is average age of coworkers' hens in neighboring production units. $food_{t-s}$ are lags of amount of food distributed as measured by 50kg sacks employed.

TABLE 3: COWORKERS' AND OWN PRODUCTIVITY

	Daily Number of Eggs per Hen, y_i			
	(1) OLS	(2) 2SLS	(3) 2SLS	(4) 2SLS
Coworkers' Eggs per Hen, $\bar{y}_{-i}$	-0.29338***	-0.30165***	-0.28778***	-0.29040***
	(0.0764)	(0.0683)	(0.0705)	(0.1004)
age_i	0.03052***	0.03043***		
	(0.0057)	(0.0060)		
age_i^2	-0.00030***	-0.00030***		
	(0.0001)	(0.0001)		
$food_{t-1}$	0.00431***	0.00430***	0.00404***	0.00411***
	(0.0012)	(0.0012)	(0.0011)	(0.0012)
$food_{t-2}$	0.00274***	0.00273***	0.00249***	0.00262***
	(0.0011)	(0.0011)	(0.0009)	(0.0010)
$food_{t-3}$	0.00268**	0.00267**	0.00217**	0.00221**
	(0.0011)	(0.0011)	(0.0010)	(0.0011)
1st Stage F-stat	n.a.	43.66	46.90	60.12
Shed-Week FEs	Y	Y	Y	Y
Age Dummies	N	N	Y	Y
Day FEs	Y	Y	Y	Y
Worker FEs	Y	Y	Y	Y
Batch FEs	N	N	N	Y
Observations	21206	21206	21206	21206
R^2	0.892	0.893	0.919	0.928

Notes. (* p-value<0.1; ** p-value<0.05; *** p-value<0.01) (1), OLS estimates; (2)-(4) 2SLS estimates. Sample is restricted to all production units in sheds with at least one other production unit. Two-way clustered standard errors, with residuals grouped along both shed and day. Dependent variable is the average number of eggs per hen collected by the worker. Main variable of interest is average daily number of eggs per hen collected by coworkers in neighboring production units, $\bar{y}_{-i}$. age_i is own hens' age in weeks. In (2) average age of coworkers' hens and its square $(\overline{age}_{-i}, \overline{age}^2_{-i})$ are used as instruments in the first stage. The full set of coworkers' hens' age dummies is used in the first stage in (3) and (4). $food_{t-s}$ are lags of amount of food distributed as measured by 50kg sacks employed.

TABLE 4: FEEDING EFFORT AND OUTPUT QUALITY

	Food (gr)	Good/Total	Broken/Total	Dirty/Total	Deaths/Hens
	(1)	(2)	(3)	(4)	(5)
Coworkers'	-34.88524	-0.15403***	0.00948	0.06619**	-0.01624
Eggs per Hen, $\bar{y}_{-i}$	(60.7982)	(0.0416)	(0.0131)	(0.0323)	(0.0167)
$food_{t-1}$	0.38861	0.00176***	-0.00031***	-0.00096***	0.00003
	(0.6388)	(0.0005)	(0.0001)	(0.0003)	(0.0001)
$food_{t-2}$	1.09963**	0.00109**	-0.00011	-0.00070**	-0.00020**
	(0.5424)	(0.0005)	(0.0001)	(0.0003)	(0.0001)
$food_{t-3}$	0.33709	0.00002	-0.00005	-0.00018	-0.00003
	(0.2755)	(0.0005)	(0.0001)	(0.0003)	(0.0001)
1st Stage F-stat	60.12	23.74	23.74	23.74	116.79
Shed-Week FEs	Y	Y	Y	Y	Y
Age Dummies	Y	Y	Y	Y	Y
Day FEs	Y	Y	Y	Y	Y
Worker FEs	Y	Y	Y	Y	Y
Batch FEs	Y	Y	Y	Y	Y
Outcome Mean	22.351	0.857	0.024	0.059	0.001
Observations	21206	21035	21035	21035	19679
R^2	0.235	0.846	0.907	0.714	0.270

Notes. (* p-value<0.1; ** p-value<0.05; *** p-value<0.01) 2SLS estimates. Sample is restricted to all production units in sheds with at least one other production unit. Two-way clustered standard errors, with residuals grouped along both shed and day. Dependent variable are: average daily amount of food in grams distributed (1), fraction of good eggs over the total (2), fraction of broken eggs over the total (3), fraction of dirty eggs over the total (4), fraction of hens dying in the day (5). Main variable of interest is average daily number of eggs per hen collected by coworkers in neighboring production units, $\bar{y}_{-i}$. The full set of own hens' age dummies are included as controls, while the full set of coworkers' hens' age dummies is used in the first stage in all specifications. $food_{t-s}$ are lags of amount of food distributed as measured by 50kg sacks employed.

TABLE 5: ROBUSTNESS CHECKS AND EFFECT HETEROGENEITY

	Daily Number of Eggs per Hen, y_i					
	(1)	(2)	(3) $\ln y_i$	(4)	(5) High Ability	(6) Low Ability
Other Shed Workers' Eggs per Hen, $\tilde{y}_{-i}$	0.00680 (0.0402)					
Non-neighboring Workers' Eggs per Hen, $\tilde{y}_{-i}$		-0.01734 (0.0567)				
Coworkers' Eggs per Hen, $\bar{y}_{-i}$			-1.47172*** (0.3734)	-0.28373*** (0.0661)	-0.01841 (0.0601)	-0.25628*** (0.0891)
$food_{t-1}$	0.00414***	0.00458***	0.01271***	0.00411***	0.00305***	0.00543***
	(0.0012)	(0.00122)	(0.0043)	(0.0012)	(0.0012)	(0.0020)
$food_{t-2}$	0.00276***	0.00298***	0.01125***	0.00263***	0.00205***	0.00275**
	(0.0010)	(0.00080)	(0.0038)	(0.0010)	(0.0007)	(0.0013)
$food_{t-3}$	0.00240**	0.00218***	0.00986**	0.00222**	0.00154**	0.00395**
	(0.0011)	(0.00080)	(0.0040)	(0.0011)	(0.0006)	(0.0017)
1st Stage F-stat	11.01	40.71	60.12	29.56	22.27	232.50
Shed-Week FEs	Y	Y	Y	Y	Y	Y
Age Dummies	Y	Y	Y	Y	Y	Y
Day FEs	Y	Y	Y	Y	Y	Y
Worker FEs	Y	Y	Y	Y	Y	Y
Batch FEs	Y	Y	Y	Y	Y	Y
Observations	20223	8294	21206	21206	10024	11168
R^2	0.926	0.887	0.900	0.928	0.960	0.953

Notes. (* p-value$<$0.1; ** p-value$<$0.05; *** p-value$<$0.01) 2SLS estimates. Sample is restricted to all production units in sheds with at least one other production unit. Subsamples in (5) and (6) are derived as discussed in Section 5.4. Two-way clustered standard errors, with residuals grouped along both shed and day. Dependent variable is average number of eggs per hen collected by the worker in all columns but (3), where the log of its value augmented by 0.01 is considered. Main variable of interest in (1) is average daily number of eggs per hen collected by coworkers in adjacent shed; in (2) is average daily number of eggs per hen collected by coworkers in the same shed, but in non-neighboring production units; in (3) to (6) is average daily number of eggs per hen collected by coworkers in neighboring production units, $\bar{y}_{-i}$. The full set of own hens' age dummies are included as controls. The full set of coworkers' hens' age dummies is used in the first stage in all columns but (4), where expected hens' productivity per week of age as reported by bird producer is used as instrument. $food_{t-s}$ are lags of amount of food distributed as measured by 50kg sacks employed.

TABLE 6: TERMINATION POLICY

	Logit of Termination Probability (Coefficients)					
	Values at time t			Moving Averages $[t-7,t]$		
	(1)	(2)	(3)	(4)	(5)	(6)
y_{it}	-6.458***	-8.130***	-11.483***	-9.355***	-12.572***	-14.056***
	(2.410)	(2.689)	(4.413)	(3.633)	(3.733)	(4.380)
$\bar{y}_{-it}$	-6.160***	-7.300***	-8.466***	-2.276	-3.483*	-7.488***
	(2.147)	(2.307)	(2.078)	(1.770)	(1.826)	(2.648)
$y_{it} \times \bar{y}_{-it}$	10.039***	12.591***	13.420***	9.645**	13.579***	14.792***
	(2.874)	(2.736)	(5.253)	(3.891)	(3.893)	(5.285)
γ_t	$\ln t$	$t+t^2+t^3$	$t+t^2+t^3$	$\ln t$	$t+t^2+t^3$	$t+t^2+t^3$
Observations	17831	17831	17831	15863	15863	15863

Notes. (* p-value<0.1; ** p-value<0.05; *** p-value<0.01) Logit estimates. Sample is restricted to all production units in sheds with at least one other production unit. Dependent variable is dummy equal to 1 if employment relationship terminates on day t. y_{it} is own daily number of eggs per hen collected on day t or its 7-days moving average in (4) to (6), while $\bar{y}_{-it}$ is the corresponding average for coworkers in neighboring production units in the same shed. (3) and (6) are Two-stage residual inclusion estimates with bootstrapped standard errors from 100 repetitions (Terza, Basu, and Rathouz 2008).

TABLE 7: INCENTIVE HETEROGENEITY

	Daily Number of Eggs per Hen, y_i				
	(1)	(2)	(3)	(4) High Prod. Age	(5) Low Prod. age
$\bar{y}_{-i}$ × High Productivity Age	-0.11396				
	(0.3104)				
$\bar{y}_{-i}$ × Low Productivity Age	-0.22477**				
	(0.1070)				
$\bar{y}_{-i}$ × Friend		0.22158			
		(0.1729)			
$\bar{y}_{-i}$ × No Friend		-0.44713**			
		(0.2173)			
$\bar{y}_{-i}$ × Experienced			-0.64749***		
			(0.1185)		
$\bar{y}_{-i}$ × Not Experienced			0.21503		
			(0.1457)		
$\bar{y}_{-i}$ × Low Age Difference				-0.12114	-0.38748
				(0.5191)	(0.3628)
$\bar{y}_{-i}$ × High Age Difference				-0.03556	-0.47980**
				(0.1460)	(0.2241)
$food_{t-1}$	0.00489***	0.00575***	0.00461**	0.00073***	0.00412***
	(0.0015)	(0.0018)	(0.0019)	(0.0003)	(0.0012)
$food_{t-2}$	0.00320**	0.00353**	0.00288**	-0.00010	0.00281***
	(0.0013)	(0.0016)	(0.0015)	(0.0001)	(0.0009)
$food_{t-3}$	0.00317**	0.00384**	0.00300**	-0.00027	0.00191*
	(0.0013)	(0.0016)	(0.0015)	(0.0002)	(0.0012)
1st Stage F-stat	17.23	32.27	25.00	5.42	4.59
	20.59	12.31	29.14	6.04	27.57
Shed-Week FEs	Y	Y	Y	Y	Y
Day FEs	Y	Y	Y	Y	Y
Worker FEs	Y	Y	Y	Y	Y
Batch FEs	Y	Y	Y	Y	Y
Observations	21206	16590	16590	11030	10169
R^2	0.902	0.918	0.942	0.838	0.935

Notes. (* p-value<0.1; ** p-value<0.05; *** p-value<0.01) 2SLS estimates. Sample is restricted to all production units in sheds with at least one other production unit. Two-way clustered standard errors, with residuals grouped along both shed and day. Dependent variable is the average number of eggs per hen collected by the worker. Main variable of interest is average daily number of eggs per hen collected by coworkers in neighboring production units $\bar{y}_{-i}$ and its interactions. In all specifications, the average age of coworkers' hens and its square ($\overline{age}_{-i}, \overline{age}^2_{-i}$) are interacted with dummy categories and used as instruments for the corresponding endogenous interaction regressor in the first stage. $food_{t-s}$ are lags of amount of food distributed as measured by 50kg sacks employed.

TABLE 8: TERMINATION POLICY COUNTERFACTUAL: RESULTS

		α_2				
		-0.25	-0.5	-0.75	-1	-1.25
α_1	2	16.66 [13.62;18.11]	1.75 [-2.65;4.47]	-15.91 [-19.10;-14.05]	-28.33 [-30.72;-26.93]	-37.52 [-39.38;-36.42]
	3	20.06 [19.17;20.86]	19.39 [18.45;20.30]	18.06 [15.72;19.26]	7.50 [3.92;9.60]	-6.28 [-9.07;-4.63]
	4	21.45 [20.67;22.19]	21.11 [20.32;21.86]	20.69 [19.89;21.45]	20.18 [19.27;20.96]	19.04 [17.10;20.08]
	5	22.40 [21.74;23.15]	22.15 [21.48;22.89]	21.88 [21.18;22.62]	21.58 [20.86;22.32]	21.20 [20.47;21.92]
	6	23.20 [22.48;23.96]	22.96 [22.28;23.72]	22.73 [22.08;23.47]	22.50 [21.88;23.23]	22.25 [21.62;22.97]

Notes. The Table shows productivity gains and losses from counterfactual termination policy as discussed and implemented in Section 8.2. 95% Confidence Intervals in square brackets, computed using bootstrapped samples from 100 repetitions. Productivity is measured as average daily number of eggs per hen over the period. Entries are percentage change with respect to actual data, with counterfactual productivity being derived using the corresponding parameter values.

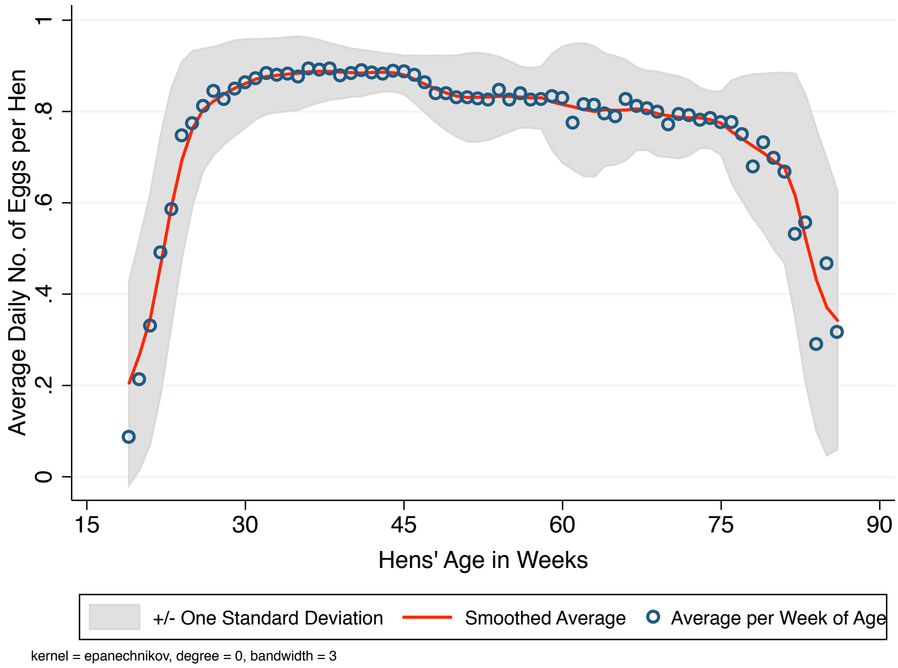
FIGURE 1: ONE SECTOR

Notes. The picture shows a given production sector in the plant under investigation. Each one of the long-shaped building is a shed.

FIGURE 2: PRODUCTION UNITS

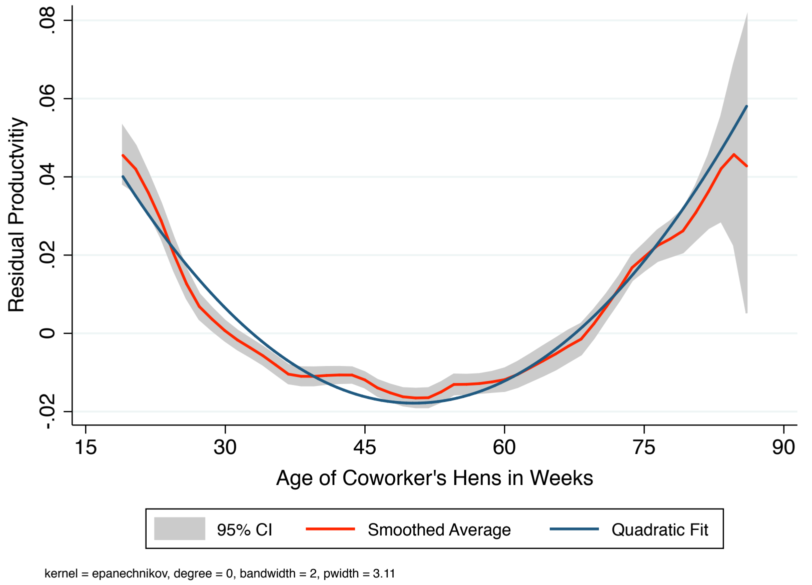
Notes. The picture of a particular shed hosting four production units. Each production unit is defined by one worker and the batch of laying hens assigned to him. We can distinguish in the picture the four production unit's warehouses located across the street from the shed.

FIGURE 3: HENS' AGE AND PRODUCTIVITY



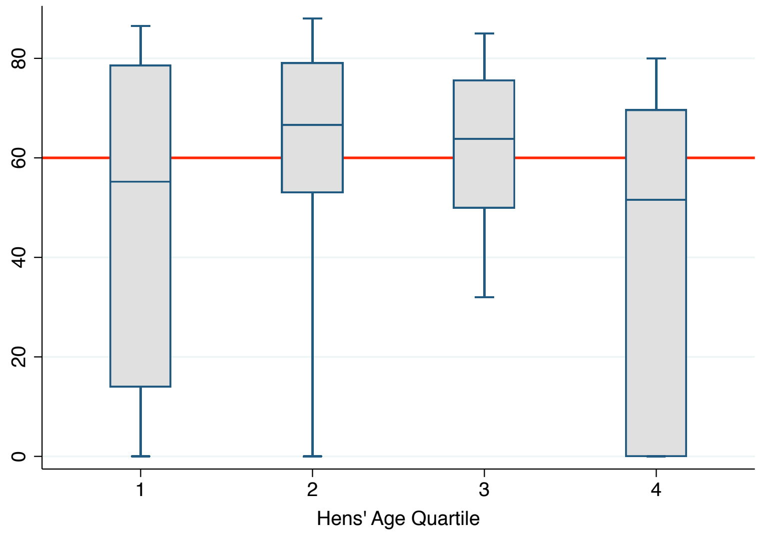
Notes. The average daily number of eggs per hen collected by the worker is plotted against the age of hens in weeks. Recall that hens in a given batch are all of the same age. The graph shows the smoothed average together with a one standard deviation interval around it. Epanechnikov kernel function is used for smoothing. Furthermore, for all given week of age, each bin in the scatterplot shows the average daily number of eggs per hen as averaged across all observations belonging to production units hosting hens of that given age. Productivity is typically low when hens are young, it reaches a peak when hens are around 40 weeks old, and then decreases thereafter until hens are old enough and the batch is discarded.

FIGURE 4: RESIDUAL PRODUCTIVITY AND AGE OF COWORKERS' HENS



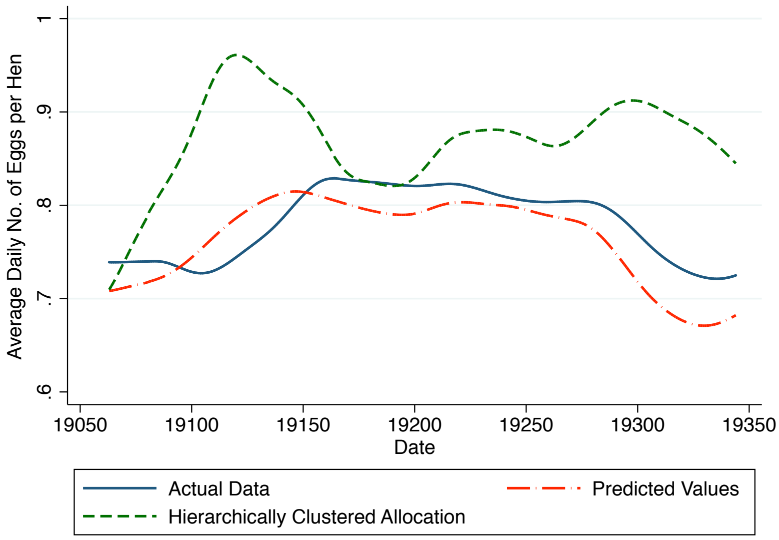
Notes. Once own hens' age, day and shed-week fixed effects are controlled for, residual productivity is plotted against the age of coworkers' hens in weeks. Productivity is measured as the average daily number of eggs per hen collected by the worker. Recall that hens in a given batch are all of the same age. The graph shows the smoothed average and its 95% confidence interval, together with the quadratic fit. Conditional on own hens' age, day and shed-week fixed, workers' residual productivity is higher (lower) when coworkers are assigned hens of low (high) productivity.

FIGURE 5: HENS' AGE AND NUMBER OF EGG BOXES



Notes. The figure plots the distribution of the average number of boxes collected by the worker in each two-weeks pay period. Within each age quartile, the bottom and top of the box correspond to the 10th and 90th percentile respectively, while the horizontal line corresponds to the mean. The ends of the vertical lines indicate the 1st and 99th percentile. The probability of reaching the bonus threshold is higher for workers whose assigned hens belong to the 2nd or 4th quartile of the age distribution, meaning of high productivity.

FIGURE 6: INPUT ALLOCATION AND PRODUCTIVITY



Notes. The figure plots the true, predicted and counterfactual average worker's productivity over time in the period under investigation. Predictions are derived starting with the batches in production in the first week of the sample, and simulating their age profiles over the period, assuming that hens were replaced after the 86th week of life. Reduced-form estimates from a fully specified model where the full sets of own and coworkers' hen's week-of-age dummies and shed-week fixed effects are included are then used to predict average daily productivity. Counterfactual productivity is derived using the same estimates, but reallocating hen batches in production in the first week of the sample among production units following a *hierarchical clustering* procedure which minimizes the variance of the age of hens within sheds. Average counterfactual productivity is higher than the actual one, and up to 20% higher than the predicted one.

Appendix A

A.1 Termination Policy and Observable Input Quality

In this section, we further extend the conceptual framework in Mas and Moretti (2009) in order to incorporate additional features of the production environment under investigation. We describe the learning process of the principal, who computes the expected workers' effort choice on the basis of available information on both output levels and observable input characteristics.

Let input quality s_i be a function of both observable and unobservable input characteristics. In particular, let

$$s_i = g(a_i)^{\eta_i} \tag{1}$$

where $g(a_i)$ is a deterministic function of hens' age whose domain is in the $(0, 1)$ interval, while η_i is an idiosyncratic random shock. The latter is independent across workers and identically distributed on the $[0, 1]$ interval according to a uniform distribution. It follows that output in a moment in time is equal to

$$y_i = g(a_i)^{\eta_i} e_i \tag{2}$$

The principal computes the expected value of individual workers' effort choices conditionally on the observed productivity y_i and the age of hens a_i assigned to the worker. The principal knows the shape of the $g(\cdot)$ function, and can thus partially net out the observable component of input contribution to output by calculating

$$\mathbb{E}\left\{g(a_i)^{\eta_i}|a_i\right\} = \int_0^1 g(a_i)^{\eta_i} d\eta_i = \frac{g(a_i) - 1}{\ln g(a_i)} > 0 \tag{3}$$

It follows that the principal divides productivity y_i by the expected input contribution in order to derive a signal z_i of the effort exerted by the worker

$$z_i = \frac{y_i}{\frac{g(a_i)-1}{\ln g(a_i)}} = \frac{g(a_i)^{\eta_i} \ln g(a_i)\ e_i}{g(a_i) - 1} > 0 \tag{4}$$

Taking logs we get

$$\ln z_i = \ln e_i + \phi(\eta_i, a_i) \tag{5}$$

where noise $\phi(\eta_i, a_i)$ is a function of both hens' age a_i and the idiosyncratic shock η_i

$$\phi(\eta_i, a_i) = \ln\left\{\frac{g(a_i)^{\eta_i} \ln g(a_i)}{g(a_i) - 1}\right\} \tag{6}$$

Let $f_i = \ln(e_i)$ and $v_i = \ln(z_i)$. The principal computes

$$\mathbb{E}\{f_i|\mathbf{v}\} = b(v_i - \bar{v}) + \bar{v} \tag{7}$$

where $b = \frac{Cov(z_i,e_i)}{Var(z_i)} < 1$. In case the noise $\phi(\eta_i, a_i)$ was normally distributed, the conditional expectation above would be the most accurate estimate of f_i. Simulations in Table A.1 and Figure A.1 show that this is indeed a reasonable assumption. Nonetheless, even when that is not the case and $\phi(\eta_i, a_i)$ was not normally distributed, the above expression for $\mathbb{E}\{f_i|\mathbf{v}\}$ would still return the predictor of f_i which minimizes the squared sum of prediction errors.

Following the conceptual framework in the paper, the probability for a given worker to keep the job is an increasing and concave function of her expected level of effort, of which f_i is a monotonic transformation. We thus have

$$q\left[\mathbb{E}\{f_i|\mathbf{v}\}\right] = q[\, b(v_i - \bar{v}) + \bar{v}\,] \tag{8}$$

with $q'(\cdot) > 0$ and $q''(\cdot) < 0$.

Notice that, since $b < 1$, the probability of keeping the job increases with both the individual signal v_i and any coworkers' signal v_{-i}. Furthermore, consistent with the empirical analysis, it can be shown that, given the expected idiosyncratic random shock $\mathbb{E}(\eta_i) = \frac{1}{2}$, signals v_i are also increasing with observable input quality $g(a_i)$.

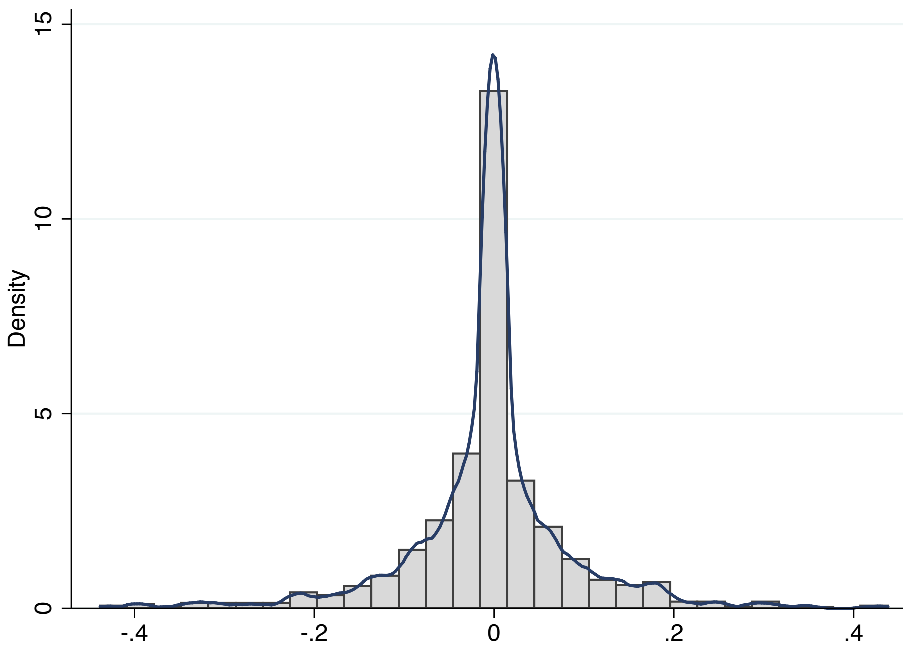
This is because, given the idiosyncratic unobservable component in input quality η_i, the principal cannot perfectly net out the input contribution to output. As a result, even observable increases in input quality increase the value of the signal the principal uses to calculate the expected level of effort exerted by the worker.

TABLE A.1: SIMULATED DISTRIBUTIONS

Variable	N	Mean	St. Dev.	Min	Max
η_i	1000	0.51	0.288	0	1
a_i	1000	54.222	19.776	20.005	89.895
$g(a_i)$	1000	0.837	0.163	0.363	1
$\phi(\eta_i, a_i)$	1000	0.002	0.085	-0.476	0.386

Notes. The Table reports summary statistics for the distributions used in the simulation exercise. In order to match the conceptual framework, η_i is generated as independently and uniformly distributed on the $[0, 1]$ interval. The hens' age variable a_i is calibrated to the data and generated as independently and uniformly distributed on the $[20, 90]$ interval. Following the results in Table 2 and assuming $e_i = 1$, the input quality variable is set as equal to $g(a_i) = 0.04a_i - 0.0004a_i^2$. The noise variable $\phi(\eta_i, a_i)$ is defined as in equation 6 of Appendix A.

FIGURE A.1: SIMULATED DISTRIBUTION OF $\phi(\eta_i, a_i)$



Notes. The figure plots the distribution of $\phi(\eta_i, a_i)$ as derived from the values of η_i, a_i and $g(a_i)$ reported in Table A.1, together its the smoothed kernel density.

A.2 Monetary and Social Incentives: Extended Conceptual Framework

This section integrates Sections 2 and 7. We derive the first order conditions which define worker's optimal effort in the presence of social and monetary incentives.

In the presence of peer pressure, the worker's problem becomes the one of choosing effort level $e_i \geq 0$ which maximizes the expected utility

$$\max_{e_i} U(\omega)\, q(y_i, \bar{y}_{-i}) - c\frac{e_i}{2}\,(e_i - \lambda\, \bar{y}_{-i}) \tag{9}$$

where $\lambda > 0$. Deriving the corresponding first order condition and applying the implicit function theorem yields

$$\frac{\partial e_i^*}{\partial \bar{y}_{-i}} = \frac{U(\omega)q_{12}(\cdot)s_i + \lambda\frac{c}{2}}{c - U(\omega)q_{11}(\cdot)s_i^2} \tag{10}$$

While the denominator of the above remains unchanged with respect to the corresponding result in the original formulation, the numerator is now ambiguous when $q_{12} < 0$. With respect to the baseline case, peer pressure pushes externalities in the opposite direction, possibly changing the sign of productivity spillovers.

In the presence of monetary incentives, the worker chooses the effort level $e_i \geq 0$ which maximizes her expected utility

$$\max_{e_i} (F + \kappa y_i)q(y_i, \bar{y}_{-i}) - c\frac{e_i^2}{2} \tag{11}$$

The corresponding first order condition is now

$$(F + \kappa y_i)q_1(\cdot)s_i + \kappa q(\cdot)s_i = ce_i \tag{12}$$

Applying the implicit function theorem we can see how optimal effort responds to coworkers' productivity in this case

$$\frac{\partial e_i^*}{\partial \bar{y}_{-i}} = \frac{(F + \kappa y_i)q_{12}(\cdot)s_i + \kappa q_2(\cdot)s_i}{c - (F + \kappa y_i)q_{11}(\cdot)s_i^2 - 2\kappa q_1(\cdot)s_i^2} \tag{13}$$

Provided that c is high enough, the denominator of the above expression is positive.[46] More importantly, the sign of the numerator is no longer uniquely determined by the sign of the cross derivative $q_{12}(\cdot)$. If the firm's implemented termination policy is such that the latter is negative, own optimal effort may still increase with coworkers'

[46] In particular, a sufficient condition for this to happen is $c > 2\kappa q_1(y_i, \bar{y}_{-i})s_i^2$ for all $s_i, y_i, \bar{y}_{-i}$.

productivity if the second term in the numerator is high enough. The latter captures how an increase in coworkers' productivity leverages the power of monetary incentives through the increase in the probability of keeping the job.

A.3 Test for Complementarity of Effort and Input Quality

In order to directly test for the complementarity of effort and input quality in the production function, we implement the following procedure. We first restrict the sample to the first quartile of the date distribution, thus focusing on those observations belonging to the earliest period in our sample. We then estimate the full set of worker fixed effects from a regression of individual productivity over worker fixed effects, the age-based expected productivity used in Column 4 of Table 5 as proxy of input quality, and the full set of batch and day fixed effects. We then restrict the sample to the last quartile of the date distribution, thus focusing on those observations belonging to the latest period in our sample, and we implement the following regression specification

$$y_{ibt} = \delta_t + \gamma_b + \alpha\, s_{bt} + \beta\, e_i + \theta\, s_{bt} \times e_i + u_{ibt} \tag{14}$$

where y_{ibt} is the average number of eggs per hen collected by worker i who is assigned hen batch b on day t, s_{bt} is the age-based time-varying proxy for input quality, and e_i is variable whose values are worker-specific and equal to the worker fixed effects estimated in the first step. δ_t and γ_b are day and hen batch fixed effects respectively.

The coefficient θ captures whether a marginal increase in input quality s_{bt} is associated with a differential productivity increase (or decrease) for high ability workers. We estimate it to be equal to 0.518, thus positive and significant at the 1% level. Evidence thus shows that the same increase in input quality is associated with a differential productivity increase for high ability workers, thus providing evidence of complementarity between input quality and worker's effort.

A.4 Counterfactual Policy Analysis: Termination Policy

This section integrates Section 8.1 and describes the procedure used to derive counterfactual productivity outcomes under alternative termination policies. Our objective is to estimate workers' average productivity under different specifications of the $q(\cdot)$ function.

In what follows, we implement our analysis within the simplified framework where workers are paid a fixed wage ω. Table 8 provides the corresponding results. We also implemented the same analysis within the extended framework where workers are paid according to a piece rate wage schedule, informing the piece rate parameters with the actual one implemented at the firm. Results are very similar to the ones presented in the paper. They are available from the authors upon request.

We start by recalling the first order condition of the worker's effort maximization problem

$$\frac{U(\omega)}{c}\, q_1(y_i, \bar{y}_{-i})\; s_i = e_i \tag{15}$$

Multiplying both sides of the expression by the input productivity variable s_i and taking logarithms we get

$$\ln y_i = \ln \frac{U(\omega)}{c} s_i^2 + \ln q_1(y_i, \bar{y}_{-i}) \tag{16}$$

Assuming such relationship holds at equilibrium, our objective is to simulate daily productivity y_{it} for all workers under a new alternative policy $\tilde{q}(\cdot)$. In particular, we are interested in the productivity effect of shutting down the externalities among coworkers generated by and built in the current policy. It is thus reasonable to evaluate productivity counterfactuals under a policy of the form

$$\tilde{q}(y_{it}) = \alpha_0 + \alpha_1\, y_{it} + \alpha_2\, y_{it}^2 \tag{17}$$

with $\tilde{q}_1(\cdot) > 0$ and $\tilde{q}_{11}(\cdot) \leq 0$. We can thus substitute the first derivative of the alternative policy function $\tilde{q}_1(\cdot)$ in the above equation and get

$$\ln y_{it} = \ln \frac{U(\omega)}{c} s_{it}^2 + \ln(\alpha_1 + 2\alpha_2\, y_{it}) \tag{18}$$

where input quality s_{it} is now allowed to vary over time.

However, notice that the first term on the RHS of the above equation is not observable in the data, so that the policy counterfactual cannot be computed directly by solving the above for y_{it}. In order to overcome this issue, we start from estimating the actual termination policy function $q(\cdot)$ by regressing a dummy q_{it} equal to one when the worker is not dismissed (and thus observed to be at work the day after) over a third order polynomial time trend $t + t^2 + t^3$ and a third order polynomial of own and coworkers' productivity $(y_{it}, \bar{y}_{-it})$. We then use the corresponding parameter estimates and actual productivity values to compute the derivative of the function with respect to y_{it}. We obtain an estimate $\hat{q}_{1,it}$ of the marginal returns from own productivity in terms of probability of keeping the job, which can be replaced in the rearranged expression of worker's first order condition. Splitting further the first term of the RHS we get

$$\ln y_{it} = \ln U(\omega) + \ln s_{it}^2 + \ln \hat{q}_{1,it} - \ln c_i \tag{19}$$

where the effort cost parameter c_i is allowed to vary across workers. This equation can be estimated through the following regression specification

$$\ln y_{it} = \alpha + \psi_{wi} + \beta \ \ln \hat{q}_{1,it} + \theta_i + \varepsilon_{it} \tag{20}$$

where we use the full set of hens' week-of-age dummies ψ_{wi} as a proxy for the input quality term $\ln s_{it}^2$ and let worker fixed effects θ_i capture the variability in $\ln c_i$. It follows that

$$\widehat{\ln y_{it}} - \hat{\beta} \ \ln \hat{q}_{1,it} = \hat{\alpha} + \hat{\psi}_{wi} + \hat{\theta}_i = \hat{m}_{it} \tag{21}$$

where $m_{it} = \ln \frac{U(\omega)}{c_i} s_{it}^2$. Following (17), worker's productivity under the alternative policy $\tilde{q}(\cdot)$ can finally be estimated through solving the following equation for y_{it}

$$\ln y_{it} = \hat{m}_{it} + \ln(\alpha_1 + 2\alpha_2 \ y_{it}) \tag{22}$$

We provide numerical solutions to the above equation, thus estimating the daily number of eggs per hen collected by the worker over the period under $\tilde{q}(\cdot)$. Table 8 shows counterfactual productivity gains and losses as predicted under the alternative termination policy, following the procedure described above.

Appendix B for Online Publication

TABLE B.1: 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

TABLE B.2: COWORKERS' AND OWN HEN'S AGE: CONDITIONAL CORRELATION

	Correlation Coefficients (1)	Correlation Coefficients (2)
Corr $(age_{igwt}, \overline{age}_{-igwt})$	0.8858	0.0066
p-value	(0.0000)	(0.5366)
Day FEs	Y	Y
Shed-Week FEs	N	Y
Observations	11231	11231

	Own Hens' Age, age_{igwt}
$\overline{age}_{-igwt}$	-0.017
	(0.034)
$\overline{age}_{-igw}$	-0.348
	(0.036)
Day FEs	Y
Shed-Week FEs	Y
Observations	22162

Notes. The top panel reports estimates of the correlation between the age of hens assigned to workers age_{igwt} and the average of hens assigned to coworkers in neighboring production units in the same shed on the same day $\overline{age}_{-igwt}$. Age variable is in weeks. When estimating conditional correlations, in order to solve for the mechanical negative bias discussed in the paper, one production unit per shed-week is randomly selected and included in the estimation sample (Bayer, Ross, and Topa 2008). Regression results in the bottom panel are based on Guryan, Kroft, and Notowidigdo (2009) as discussed in the paper. As before, $\overline{age}_{-igwt}$ is average age of hens assigned to coworkers in neighboring production units on the same day, while $\overline{age}_{-igw}$ is the average value for peers in the same shed in all days of the week. Two-way clustered standard errors are estimated, with residuals grouped along both shed and day. Sample is restricted to all production units in sheds with at least one other production unit.

TABLE B.3: COWORKER'S BATCH REPLACEMENT AND PAST PRODUCTIVITY

	Dummy for Coworker's Batch Replacement at time t						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
y_{it-1}	-0.00067	0.00273	0.00377	0.00446	0.00511	0.00461	0.00469
	(0.0035)	(0.0032)	(0.0036)	(0.0041)	(0.0035)	(0.0034)	(0.0036)
y_{it-2}		-0.00434	-0.00202	-0.00099	0.00003	-0.00000	-0.00001
		(0.0035)	(0.0019)	(0.0016)	(0.0015)	(0.0016)	(0.0015)
y_{it-3}			-0.00419	-0.00009	0.00212	0.00203	0.00199
			(0.0038)	(0.0021)	(0.0017)	(0.0019)	(0.0020)
y_{it-4}				-0.00696	-0.00238	-0.00339	-0.00347
				(0.0045)	(0.0026)	(0.0028)	(0.0028)
y_{it-5}					-0.00301	-0.00871	-0.00968
					(0.0036)	(0.0103)	(0.0113)
y_{it-6}						0.00824	0.00853
						(0.0100)	(0.0107)
y_{it-7}							0.00091
							(0.0020)
Constant	0.00043***	0.00044***	0.00045***	0.00046***	0.00026**	0.00026**	0.00027**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
F-stat							0.61
p-value							0.7453
Observations	20759	20336	19931	19540	19155	18777	18415
R^2	0.000	0.000	0.000	0.000	0.000	0.001	0.001

Notes. (* p-value<0.1; ** p-value<0.05; *** p-value<0.01) Sample is restricted to all production units in sheds with at least one other production unit. Observations are clustered at the worker level. Dependent variable is a dummy equal to one if any replacement of batches occurred in neighboring production units at time t. Regressors are the average daily number of eggs per hen collected by the workers in the previous days. Column (7) also reports the results from an F-test of joint significance of all coefficients.

TABLE B.4: OWN AND COWORKERS' HENS' AGE AND PRODUCTIVITY: ADDITIONAL RESULTS

	Daily Number of Eggs per Hen, y_i			
	(1)	(2)	(3)	(4)
age_i	0.03860***	0.03871***	0.03900***	0.03805***
	(0.0059)	(0.0058)	(0.0058)	(0.0058)
age_i^2	-0.00038***	-0.00038***	-0.00039***	-0.00038***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\overline{age}_{-i}$		-0.00135***		-0.00385***
		(0.0005)		(0.0013)
$\overline{age}^2_{-i}$			-0.00001**	0.00003**
			(0.0000)	(0.0000)
$food_{t-1}$	0.00137***	0.00139***	0.00138***	0.00140***
	(0.0005)	(0.0004)	(0.0005)	(0.0004)
$food_{t-2}$	0.00078**	0.00081***	0.00081***	0.00080***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$food_{t-3}$	-0.00001	-0.00002	-0.00002	-0.00002
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Day FEs	Y	Y	Y	Y
Shed-Week FEs	Y	Y	Y	Y
Worker FEs	N	N	N	N
Observations	20907	20907	20907	20907
R^2	0.859	0.860	0.860	0.860

Notes. (* p-value<0.1; ** p-value<0.05; *** p-value<0.01) Ordinary Least Square estimates. Sample is restricted to all production units in sheds with at least one other production unit. Two-way clustered standard errors, with residuals grouped along both shed and day. Dependent variable is the average number of eggs per hen collected by the worker. age_i is own hens' age in weeks, while $\overline{age}_{-i}$ is average age of coworkers' hens in neighboring production units. $food_{t-s}$ are lags of amount of food distributed as measured by 50kg sacks employed.

TABLE B.5: KINKED REGRESSION RESULTS

	Daily Number of Eggs per Hen, y_i				
	(1) All Segments All Ages	(2) 1st Segment Age 19 to 24	(3) 2nd Segment Age 25 to 33	(4) 3rd Segment Age 32 to 79	(5) 4th Segment Age 80 to 86
Coworkers'	-0.25854***	-0.48900	-0.14598	-0.35174	-2.11300
Eggs per Hen, $\bar{y}_{-i}$	(0.0913)	(0.6507)	(0.7686)	(0.6058)	(3.4451)
Age-kink Predicted	0.66402***	0.41955***	1.04185***	0.67574***	-1.72927
Eggs per Hen $\widehat{y}_i$	(0.0797)	(0.1153)	(0.2351)	(0.0566)	(2.8642)
$food_{t-1}$	0.00432***	0.00091	0.00137	0.00495***	0.01253
	(0.0011)	(0.0012)	(0.0012)	(0.0017)	(0.0082)
$food_{t-2}$	0.00262***	0.00175	0.00031	0.00182*	0.01079
	(0.0009)	(0.0011)	(0.0015)	(0.0011)	(0.0119)
$food_{t-3}$	0.00225**	0.00246**	0.00182***	0.00169	-0.01054
	(0.0010)	(0.0012)	(0.0005)	(0.0011)	(0.0320)
1st Stage F-stat	57.37	2.03	1.96	3.50	0.12
Shed-Week FEs	Y	Y	Y	Y	Y
Day FEs	Y	Y	Y	Y	Y
Worker FEs	Y	Y	Y	Y	Y
Batch FEs	Y	Y	Y	Y	Y
Observations	21206	2423	3882	14543	347
R^2	0.913	0.962	0.949	0.853	0.571

Notes. (* p-value<0.1; ** p-value<0.05; *** p-value<0.01) 2SLS estimates. Sample is restricted to all production units in sheds with at least one other production unit. Two-way clustered standard errors, with residuals grouped along both shed and day. Dependent variable is the average number of eggs per hen collected by the worker. Main variable of interest is average daily number of eggs per hen collected by coworkers in neighboring production units, $\bar{y}_{-i}$. A linear function of age with three kinks is used to predict own productivity and as instrument for coworkers' productivity, as computed from own and coworkers' hens' age respectively. Column (1) shows results using the overall sample. Columns (2) to (5) show results separately for each one of the four segments of the linear function, thus splitting the sample according to the age interval coworkers' hens belong to. $food_{t-s}$ are lags of amount of food distributed as measured by 50kg sacks employed.

TABLE B.6: BATCH OR WORKER REPLACEMENT AND FURTHER ROBUSTNESS CHECKS

	Daily Number of Eggs per Hen, y_i						
	(1) Batch Replacement	(2) No Batch Replacement	(3) Worker Replacement	(4) No Worker Replacement	(5) No Batch/Worker Replacement	(6) Angrist (2014)	(7) No Absentees
Coworkers'	-0.32766**	-0.31678***	0.33676	-0.30498***	-0.31853***	-0.47200***	-0.28468***
Eggs per Hen, $\bar{y}_{-i}$	(0.1665)	(0.0723)	(0.3861)	(0.0660)	(0.0731)	(0.1346)	(0.0993)
age_i	-0.00683	0.02908***	0.21441***	0.03062***	0.02923***		
	(0.1332)	(0.0069)	(0.0638)	(0.0060)	(0.0070)		
age_i^2	-0.00027	-0.00029***	-0.00218***	-0.00030***	-0.00029***		
	(0.0013)	(0.0001)	(0.0007)	(0.0001)	(0.0001)		
$food_{t-1}$	0.00037	0.00439***	0.01330*	0.00425***	0.00434***	0.00982***	0.00415***
	(0.0017)	(0.0012)	(0.0069)	(0.0012)	(0.0012)	(0.0020)	(0.0012)
$food_{t-2}$	-0.00036	0.00259**	0.00718	0.00266**	0.00251**	0.00496***	0.00251**
	(0.0163)	(0.0011)	(0.0072)	(0.0010)	(0.0010)	(0.0016)	(0.0010)
$food_{t-3}$	0.02167	0.00255**	-0.00258	0.00268**	0.00257**	0.00631***	0.00223**
	(0.0235)	(0.0011)	(0.0020)	(0.0011)	(0.0011)	(0.0016)	(0.0010)
1st Stage F-stat	30.81	16.45	3.63	43.22	16.30	40.83	48.70
Shed-Week FEs	Y	Y	Y	Y	Y	Y	Y
Age Dummies	N	N	N	N	N	Y	Y
Day FEs	Y	Y	Y	Y	Y	Y	Y
Worker FEs	Y	Y	Y	Y	Y	Y	Y
Batch FEs	Y	Y	Y	Y	Y	Y	Y
Observations	134	21070	311	20895	20759	8583	20882
R^2	0.978	0.894	0.991	0.891	0.892	0.973	0.927

Notes. (* p-value$<$0.1; ** p-value$<$0.05; *** p-value$<$0.01) 2SLS estimates. Sample is restricted to all production units in sheds with at least one other production unit. Two-way clustered standard errors, with residuals grouped along both shed and day. Subsample in (1) contains observations belonging to production units and weeks with batch replacement for either the worker or her coworkers. Subsample in (2) contains observations belonging to production units and weeks with no batch replacement for either the worker or the coworkers. Subsample in (3) contains observations belonging to weeks and sheds with any employment termination recorded among the workers in the shed. Subsample in (4) contains observations belonging to weeks and sheds without any employment termination recorded among the workers in the shed. Subsample in (5) contains observations belonging to weeks and production units without any batch replacement for either the worker or the coworkers, and without any employment termination recorded among the workers in the shed. A random sample of production units per shed-week is considered in column (3). Subsample excluding observations belonging to days where worker was listed as absent is considered in column (4). Dependent variable is the average number of eggs per hen collected by the worker. Main variable of interest is average daily number of eggs per hen collected by coworkers in neighboring production units, $\bar{y}_{-i}$. age_i is own hens' age in weeks. In (1) and (2) average age of coworkers' hens and its square $(\overline{age}_{-i}, \overline{age}^2_{-i})$ are used as instruments in the first stage. The full set of coworkers' hens' age dummies is used in the first stage in (6) and (7). $food_{t-s}$ are lags of amount of food distributed as measured by 50kg sacks employed.

TABLE B.7: TERMINATION POLICY - TOTAL NUMBER OF EGGS

	Logit of Termination Probability (Coefficients)					
	Values at time t			Moving Averages $[t-7, t]$		
	(1)	(2)	(3)	(4)	(5)	(6)
Y_{it}	-0.331***	-0.402***	-1.060***	-0.199*	-0.329***	-0.979**
	(0.087)	(0.089)	(0.388)	(0.103)	(0.099)	(0.410)
$\bar{Y}_{-it}$	-0.411***	-0.478***	-0.721***	-0.248**	-0.364***	-0.751***
	(0.099)	(0.103)	(0.149)	(0.103)	(0.102)	(0.194)
$Y_{it} \times \bar{Y}_{-it}$	0.039***	0.048***	0.105***	0.020	0.035***	0.095**
	(0.011)	(0.011)	(0.039)	(0.013)	(0.019)	(0.040)
γ_t	$\ln t$	$t + t^2 + t^3$	$t + t^2 + t^3$	$\ln t$	$t + t^2 + t^3$	$t + t^2 + t^3$
Observations	17831	17831	17831	15863	15863	15863

Notes. (* p-value<0.1; ** p-value<0.05; *** p-value<0.01) Logit estimates. Sample is restricted to all production units in sheds with at least one other production unit. Dependent variable is dummy equal to 1 if employment relationship terminates on day t. Y_{it} is own total number of eggs collected on day t in thousands or its 7-days moving average in (4) to (6), while $\bar{Y}_{-it}$ is the corresponding average for coworkers in neighboring production units in the same shed. (3) and (6) are Two-stage residual inclusion estimates with bootstrapped standard errors from 100 repetitions (Terza, Basu, and Rathouz 2008).

TABLE B.8: TERMINATION POLICY - ADDITIONAL EVIDENCE

	Logit of Termination Probability (Coefficients)				
	(1)	(2)	(3)	(4)	(5)
Y_{gt}	-0.209***	-0.210***	-0.209***	-0.215***	-0.209***
	(0.021)	(0.021)	(0.021)	(0.022)	(0.021)
$Y_{igt} - Y_{-igt}$		0.041		-0.067	
		(0.045)		(0.108)	
$y_{igt} - y_{-igt}$			0.167		0.794
			(0.546)		(0.940)
$Y_{gt} \times (Y_{igt} - Y_{-igt})$				0.011	
				(0.010)	
$Y_{gt} \times (y_{igt} - y_{-igt})$					-0.137
					(0.167)
γ_t	$t + t^2 + t^3$	$t + t^2 + t^3$	$t + t^2 + t^3$	$t + t^2 + t^3$	$t + t^2 + t^3$
Observations	17831	17831	17831	17831	17831

Notes. (* p-value<0.1; ** p-value<0.05; *** p-value<0.01) Logit estimates. Sample is restricted to all production units in sheds with at least one other production unit. Dependent variable is dummy equal to 1 if employment relationship terminates on day t. Y_{gt} is the total number of eggs collected on day t in shed g in thousands. y_{igt} is own total number of eggs collected on day t, while $\bar{y}_{-igt}$ is the corresponding average for coworkers in neighboring production units in the same shed. Y_{igt} is own total number of eggs collected on day t in thousands, while $\bar{Y}_{-igt}$ is the corresponding average for coworkers in neighboring production units in the same shed.

TABLE B.9: PAY: SUMMARY STATISTICS

Variable	N	Mean	St. Dev.	Min	Max
Base Pay (PEN)	1470	505.52	66.39	26.5	704
Bonus Pay (PEN)	1470	81.77	50.28	0	442
Total Pay (PEN)	1470	588.65	89.34	29.5	972

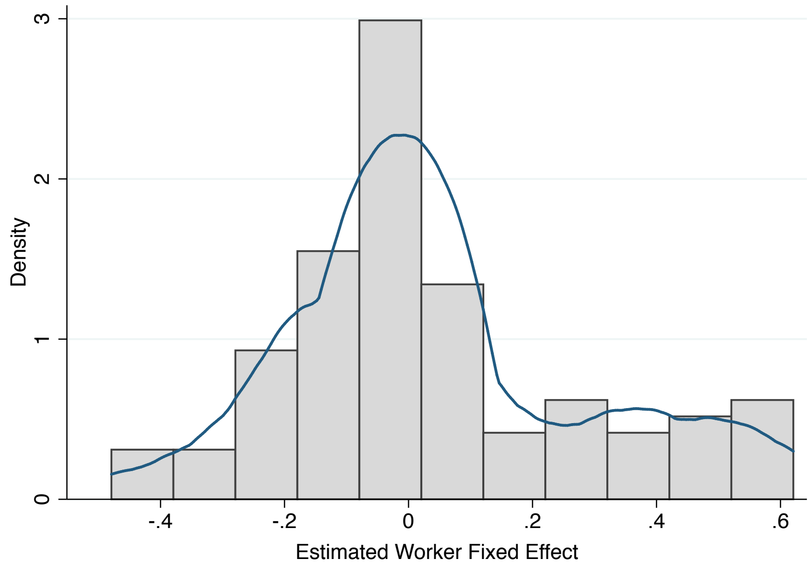
Notes. The Table reports summary statistics for the pay data. Workers are paid every two weeks. The wage formula is presented and discussed in Section 7 of the paper. The bonus component is calculated using the number of eggs boxes produced in a randomly chosen day within the same two weeks. 1 PEN = 0.38 USD (June 30, 2012), with minimum wage in the period being 750 PEN (285 USD).

TABLE B.10: HENS' AGE AND BONUS PAY

	Averages across Hens' Age Distribution			
	1st Quartile	*2nd Quartile*	*3rd Quartile*	*4th Quartile*
Base Pay (PEN)	508.25	518.75	522.06	513.51
Bonus Pay (PEN)	86.75	104.42	88.43	66.57
Total Pay (PEN)	596.93	624.05	612.16	581.07

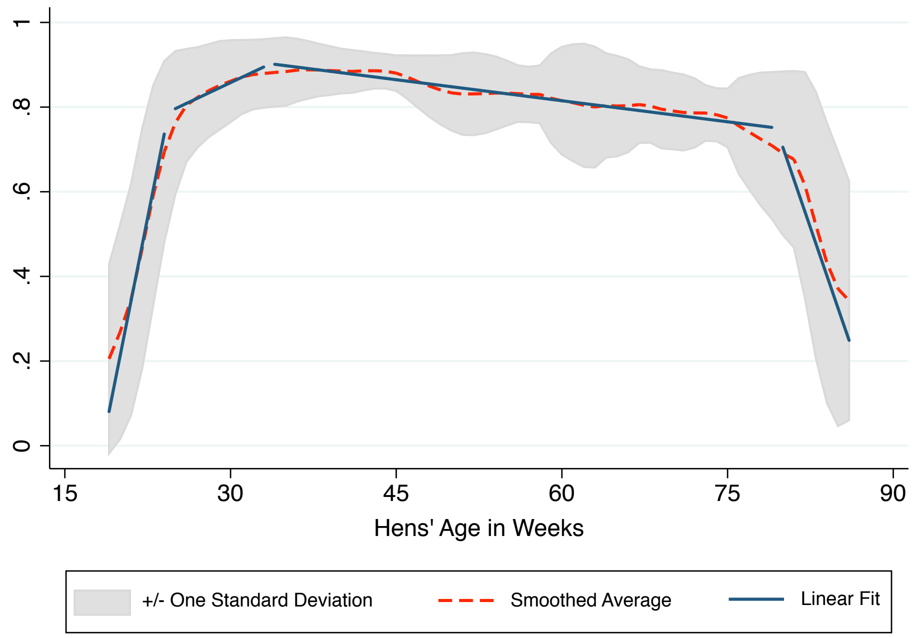
Notes. Average bonus pay per quartiles of hens' age distribution. 1 PEN = 0.38 USD (June 30, 2012).

FIGURE B.1: DISTRIBUTION OF ESTIMATED WORKER FIXED EFFECTS



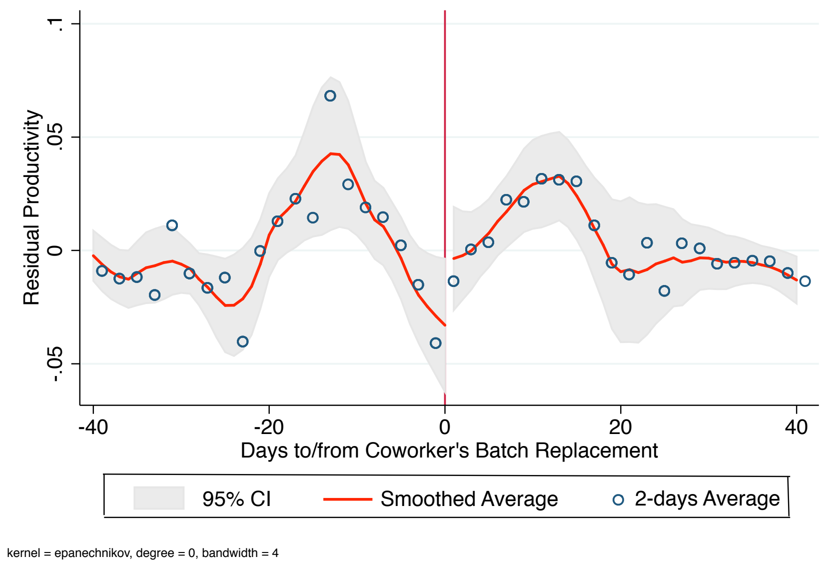
Notes. The figure plots the distribution of worker fixed effects as estimated from a regression specification where hens' week-of-age dummies, batch and day fixed effects are also included as regressors. Conditional on input quality, workers have a substantial impact on productivity.

FIGURE B.2: HENS' AGE AND PRODUCTIVITY: KINKED REGRESSION FIT



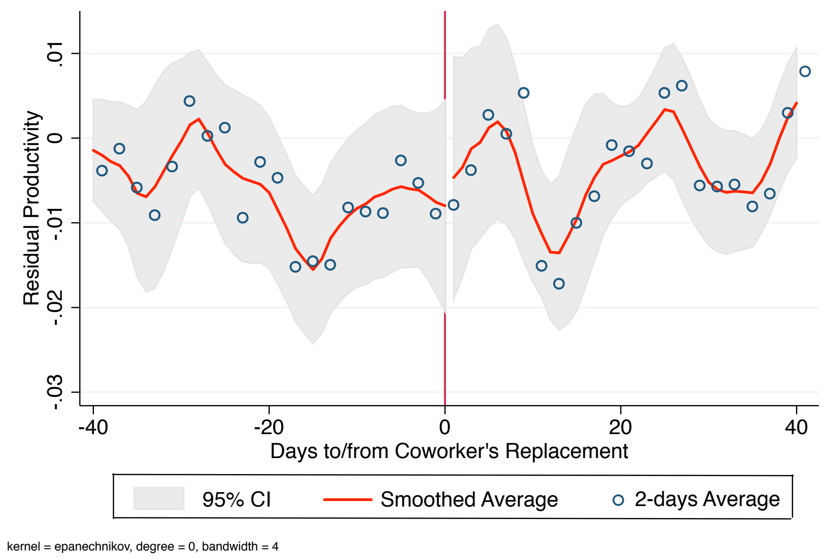
Notes. The average daily number of eggs per hen collected by the worker is plotted against the age of hens in weeks. Recall that hens in a given batch are all of the same age. The graph shows the smoothed average together with a one standard deviation interval around it. Epanechnikov kernel function is used for smoothing. Furthermore, the figure shows the average daily number of eggs per hen as predicted by a kinked regression with 3 kinks. The values of hens' age to which the three kinks correspond are chosen so to maximize the R^2 of the regression.

FIGURE B.3: RESIDUAL PRODUCTIVITY AND COWORKER'S BATCH REPLACEMENT



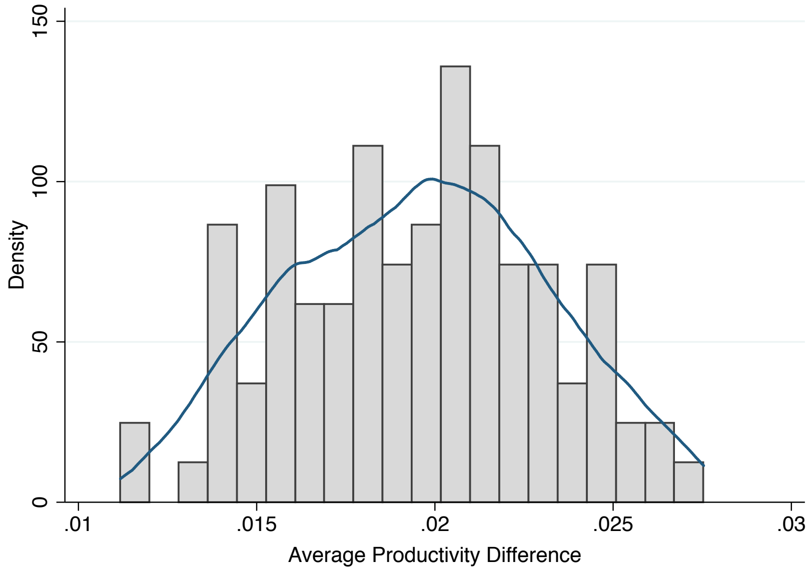
Notes. Residual productivity net of own hens' age is plotted over time around the day of coworker's batch replacement. Productivity is measured as the average daily number of eggs per hen collected by the worker. The graph plots the smoothed average and its 95% confidence interval separately in the days before and after coworker's batch replacement. Evidence shows that there is no systematic and discontinuous change in residual productivity at the time of replacement.

FIGURE B.4: RESIDUAL PRODUCTIVITY AND COWORKER REPLACEMENT



Notes. Residual productivity net of own hens' age is plotted over time around the day a neighboring coworker is replaced by a new one. Productivity is measured as the average daily number of eggs per hen collected by the worker. The graph plots the smoothed average and its 95% confidence interval separately in the days before and after coworker replacement. Evidence shows that there is no systematic and discontinuous change in residual productivity at the time of replacement.

FIGURE B.5: RANDOM INPUT ALLOCATION AND PRODUCTIVITY



Notes. The figure plots the distribution of the difference between the average productivity of workers throughout the sample period and the counterfactual average productivity obtained under 100 alternative scenarios where hen batches in production in the first week of the sample are randomly assigned to production units. Their age profiles are then simulated over the period assuming that hens were replaced after the 86th week of life. The difference is always positive, with a mean of 0.0195 and a standard deviation of 0.003. The average difference is thus significantly different from zero at the 5% level.