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

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Abstract

This paper shows how input heterogeneity triggers 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 the provision of 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: input heterogeneity, productivity, spillovers, termination, incentives.

JEL Codes: D22, D24, D61, J24, J33, M11, M52, M54, O12.

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1 Introduction

Differences in management practices explain a considerable amount of variation in firms' productivity and performance. Given the same inputs, better managed firms achieve higher sales value and growth, capital returns and survival probabilities compared to less well-managed ones, both within and across sectors and countries (Bloom and Van Reenen 2007, 2010; Bloom, Mahajan, McKenzie, and Roberts 2010; Bloom, Eifert, Mahajan, McKenzie, and Roberts 2013).

In particular, a number of studies show how human resource management practices may affect productivity through the externalities they generate among coworkers in their choice of effort. In their pioneering work, Bandiera, Barankay, and Rasul (2005) use personnel data from a leading fruit producer in the UK to show how fruit picking workers internalize the negative externalities generated by a relative performance evaluation pay scheme. As a result, average productivity increases by at least 50% when piece rate pay is introduced. More recently, Mas and Moretti (2009) investigate productivity spillovers among cashiers in a large US supermarket chain. Social pressure from working peers is there shown to be strong enough to offset the negative externalities that the worker evaluation and firing policy is assumed to generate. These studies show how, even in the absence of technological sources of externalities, personnel policies can make coworkers' choices of effort interdependent and generate productivity spillovers.

However, much less is known about how these arguments generalize and apply to more complex production environments. Workers often produce output by combining their effort with inputs of heterogeneous quality. Inputs of higher quality increase the marginal product of effort. For instance, 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 whether and how the productivity of workers is affected by peers' productivity in those contexts where workers 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. Is there any evidence of productivity spillovers of this origin? Do human resource management practices shape the size and sign of these spillovers?

Answering these questions 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.

Along with the identification of productivity spillovers from heterogeneous inputs, we use both theory and empirics to identify the specific source of externalities in this setting. We focus on the role of human resource management practices, and, in particular, the worker evaluation and dismissal policies implemented by the firm. We build upon Mas and Moretti (2009), and provide a simple conceptual framework to 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 is more likely to induce 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. Consistently 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 is heterogeneous according to the workers' friendship status. Consistently 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.

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 investi-

[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 5.1 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 5.2 and Appendix A.1.

gates the externalities generated by human resource management practices. Bandiera, Barankay, and Rasul (2005) explicitly 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 the first comprehensive analysis of managerial incentives, investigating their impact on productivity through endogenous team formation, and the consequences for lower-tier workers who are socially connected to managers. More recently, Bandiera, Barankay, and Rasul (2013) provide a theoretical and empirical investigation 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 represent the first attempt to study the role of heterogeneous inputs and their allocation to working peers in triggering 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 in determining 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. Estimating the unobserved exogenous parameters of the model, we are able to conduct counterfactual policy analyses. Holding everything else constant, we estimate the implementation of alternative input assignment schedules to bring about up to 20% productivity gains. By the same token, the implementation of alternative termination policies is estimated to 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. 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.

A number of other studies investigate the issue of productivity spillovers in a variety of settings. Gould and Winter (2009) focus on production externalities which are built in the technology of baseball teams. They show the sign of effort externalities among players in substitute or complement roles to be consistent with theoretical expectations. Arcidiacono, Kinsler, and Price (2013) estimate spillovers in basketball teams, highlighting the role of heterogeneity in the positive spillovers generated by individual players, and discussing its implications for worker evaluation and team performance. Brown (2011) exploits instead variation in the presence of superstars in professional golf tournaments to identify competition externalities. She finds the presence of superstars to negatively affect the effort exerted by contestants. However, Guryan, Kroft, and Notowidigdo (2009) previously found no average effect of other players' ability on own effort among professional golf players, attributable to the incentives determined by the steep prize structure. Cornelissen, Dustmann, and Schönberg (2013) use German social security data and exploit variation in one's working peers throughout her working life in order to identify productivity spillovers. They find only small peer effects on wages.

More generally, and in light of the identification challenges we face, our paper contributes to the literature on empirical analysis of peer effects. After the seminal work of Manski (1993), a number of studies have delved into the empirics of social interactions mechanisms.[2] While our empirical analysis is carried out using the tools which are peculiar of the peer effects literature, our study nonetheless focuses on productivity spillovers of different nature. In our context, these are triggered by the heterogeneity in inputs assigned to workers. We thus regard our analysis and results as complementary to the peer effects literature, possibly opening the way to a joint exploration of productivity spillovers of mixed nature.

The rest of the paper is organized as follows. Section 2 provides the details of the setting. The data and the relevant baseline statistics are presented in Section 3. Section 4 shows the results from the empirical analysis, together with robustness checks and estimates of effect heterogeneity. The relevant mechanism and conceptual framework are presented in Section 5, together with the corresponding empirical analysis. The impact of monetary and social incentives is discussed in Section 6, while Section

[2]For a recent survey of the empirics of social interactions, see Ioannides and Topa (2010) and Blume, Brock, Durlauf, and Ioannides (2011).

7 presents the counterfactual analyses of alternative input assignment schedules and dismissal policies. Section 8 concludes.

2 The Context

Our aim is to investigate whether individual effort changes with coworkers' productivity in those contexts where workers handle inputs of heterogeneous quality. We take this question 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 Figure 1. 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.

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.

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.

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.

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.[3] Egg production establishments in developed countries are typically endowed with automatic feeders and automated gathering belts for egg handling and collection.[4] 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 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

[3]The worker's typical daily schedule is reported in Table B.1 in the 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 4. The variance of the distribution is indicative that, conditional on input quality, workers can have a substantial impact on productivity.

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

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.

3 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 100 workers are at work in the sector for at least one day, while we can identify 171 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. In this way, we can control for the variation in the number of living hens, which may by itself affect productivity.[5] The number of good, dirty, broken and porous eggs is reported as well, together with the daily number of hens dying on each day. Finally, the data also provide information on the daily amount of food handled and distributed among 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 20,915 observations, one per production unit and day. As previously mentioned, the chosen productivity measure is the daily number of eggs per living hen. Its average across the whole sample is equal to 0.78. Consistently with the setting description above, hens' age varies 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.[6] 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.

[5] 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 4. 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.

[6] 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 among the hens. This results in measurement error, and can explain why the maximum quantity of food per chicken in the data is almost 6kg.

TABLE 1: SUMMARY STATISTICS

Variable	Obs.	Mean	St. Dev.	Min	Max
Daily Eggs per Hen, y_i	20,915	0.784	0.2	0	1
Hens' Age (weeks)	20,915	45.274	16.944	19	86
No. of Hens	20,915	9,974.023	3,884.469	44	17,559
Food (50kg sacks)	20,915	22.416	8.967	0	40
Food per Chicken (g)	20,915	112.067	50.495	0	5,947.137
Good/Total	20,755	0.857	0.093	0	1
Broken/Total	20,755	0.024	0.037	0	0.357
Dirty/Total	20,755	0.059	0.049	0	1
Porous/Total	20,755	0.05	0.06	0	1
Deaths/No. of Hens	19,343	0.001	0.017	0	0.782
Daily Eggs per Hen Coworkers' Average, $\bar{y}_{-i}$	20,915	0.784	0.197	0	0.999
Hens' Age Coworkers' Average (weeks)	20,915	45.194	16.526	19	86
Dummies:					
Low Productivity Hens' Age	20,915	0.476	0.499	0	1
Working Along Friend	16,318	0.24	0.427	0	1
Experience Above Median	16,318	0.522	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.

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.

Production data are complemented with those 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.[7]

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

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 6.

4 Empirical Analysis of Productivity Spillovers

4.1 Preliminary Evidence and Identification Strategy

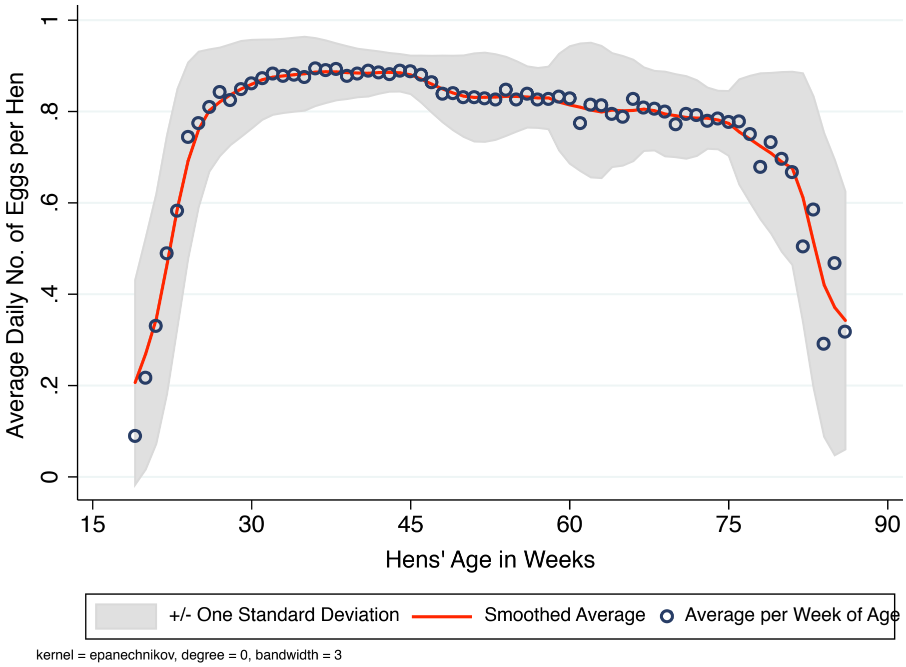
The batch of laying hens as a whole is the main production input in this context. The worker is assigned the same batch of equally aged hens from the moment they are moved to production until they are discarded. Crucially, hens' productivity varies with age. The more productive hens are the higher is the marginal product of effort. We thus regard input quality and effort as complements in production.[8] 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.[9]

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 specifica-

[8] 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.

[9] 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.

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.

tion

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

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 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.[10] 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

[10]In Section 4.2, we also use 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.

previous days.[11] 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).[12] 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 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 0.896, 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. It follows that hen batches in neighboring produc-

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

[12] 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).

tion units have approximately the same age. However, there is still residual variation to exploit. The same 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 0.53. 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.[13][14]

Evidence shows 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.[15]

4.2 Baseline Results

The first set of regression results is reported in Table 2. 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

[13]Table B.2 in 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.

[14]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 Appendix B, showing that H_0 cannot be rejected.

[15]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. 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.4 of Appendix B.

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

	Daily Number of Eggs per Hen, y_i				
	(1)	(2)	(3)	(4)	(5)
age_i	0.04076***	0.03903***	0.03859***	0.03803***	0.03249***
	(0.0024)	(0.0023)	(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)
$\overline{age}_{-i}$				-0.00387***	-0.00646***
				(0.0013)	(0.0024)
$\overline{age}^2_{-i}$				0.00003**	0.00005*
				(0.0000)	(0.0000)
$food_{t-1}$		0.00184*	0.00139***	0.00143***	0.00460***
		(0.0009)	(0.0005)	(0.0004)	(0.0012)
$food_{t-2}$		0.00093*	0.00079**	0.00082***	0.00304***
		(0.0005)	(0.0003)	(0.0003)	(0.0011)
$food_{t-3}$		0.00074	-0.00000	-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	20915	20915	20907	20907	20907
R^2	0.411	0.434	0.857	0.858	0.885

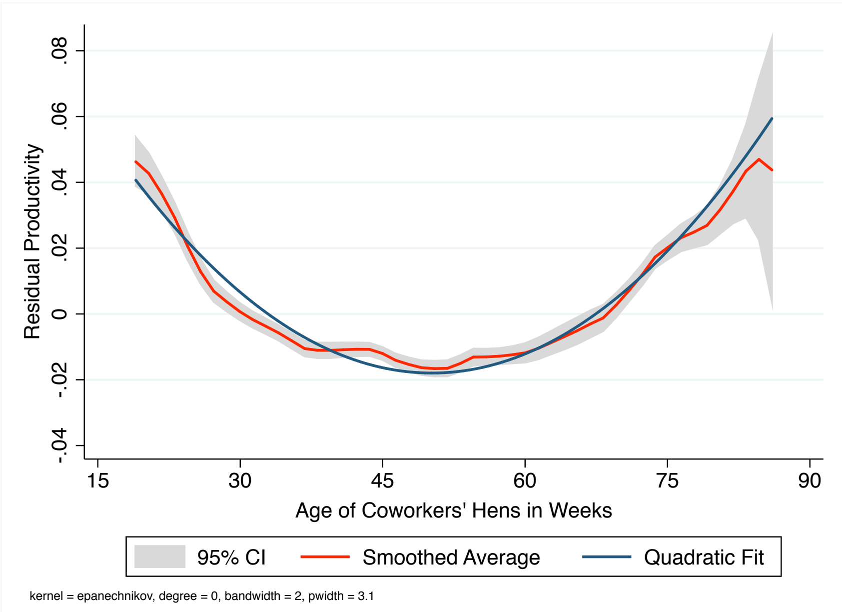
Notes. (* p-value<0.1; ** p-value<0.05; *** p-value<0.01) Ordinary Least Square estimates. Sample is restricted to all production units in sheds with at least one other production unit. Two-way clustered standard errors, with residuals grouped along both shed and day. Dependent variable is the average 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.

hens' age which is consistent with the evidence in Figure 3.[16] 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

[16] As previously mentioned, in Section 4.2 we also use hens' week-of-age dummies in order to better fit the productivity-age profile.

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 now up to 0.86.

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.

The average age of hens assigned to coworkers in neighboring production units is included in Column 4 of Table 2, together with its square.[17] 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.[18] 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

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

[18] 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.3 in the Appendix B.

with respect to the ones of own hens' age.[19] 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 0.88. Consistently 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.[20] 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 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.

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 43.68. The two instruments

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

[20] 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.

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, $\bar{y}_{-i}$	-0.29539***	-0.30258***	-0.28877***	-0.29019***
	(0.0765)	(0.0689)	(0.0697)	(0.0984)
age_i	0.03067***	0.03059***		
	(0.0057)	(0.0060)		
age_i^2	-0.00030***	-0.00030***		
	(0.0001)	(0.0001)		
$food_{t-1}$	0.00431***	0.00431***	0.00404***	0.00408***
	(0.0012)	(0.0012)	(0.0011)	(0.0012)
$food_{t-2}$	0.00277***	0.00276***	0.00252***	0.00261***
	(0.0011)	(0.0011)	(0.0009)	(0.0010)
$food_{t-3}$	0.00268**	0.00268**	0.00214**	0.00217**
	(0.0011)	(0.0011)	(0.0010)	(0.0011)
1st Stage F-stat	n.a.	43.68	27.19	251.29
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	20907	20907	20907	20907
R^2	0.891	0.891	0.918	0.927

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.

together are thus relevant in inducing variation in the regressor of interest.[21] More im-

[21] The *p-value* from the Sargan-Hansen test of overidentifying restrictions is higher than 0.10. We thus cannot reject the null hypothesis that both instruments being exogenous once one is assumed to be exogenous. However, the variables we use as instruments are both functions of the same hens' age variable, so that the rationale for this test can be questioned.

portantly, 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 of all the instrument dummies in the first stage is equal to 27.19, 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 251.29, 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.

In order to correctly interpret the above results, it is important to understand 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.

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, consistently 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.

Going beyond the negative effect on own output, the structure of the data allows 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 2.85 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.[22] Indeed, the estimated coefficient in Column 4 is significant at the 5% level and equal to 0.06: a one standard deviation increase in average coworkers' output is associated with a 1.24 percentage point increase in the own fraction of dirty eggs over the total. 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. Overall, results from Table 4 suggest coworkers' productivity

[22] Recall that workers can turn a dirty egg into a good egg by cleaning it.

TABLE 4: FEEDING EFFORT AND OUTPUT QUALITY

	Food (gr)	Good/Total	Broken/Total	Dirty/Total	Deaths/Total
	(1)	(2)	(3)	(4)	(5)
Coworkers'	-40.79075	-0.15111***	0.01154	0.06285**	-0.01586
Eggs per Hen, $\bar{y}_{-i}$	(61.9546)	(0.0415)	(0.0131)	(0.0318)	(0.0169)
$food_{t-1}$	0.39094	0.00173***	-0.00030***	-0.00095***	0.00003
	(0.6379)	(0.0005)	(0.0001)	(0.0003)	(0.0001)
$food_{t-2}$	1.12516**	0.00107**	-0.00012	-0.00069**	-0.00020**
	(0.5456)	(0.0005)	(0.0001)	(0.0003)	(0.0001)
$food_{t-3}$	0.33582	0.00003	-0.00005	-0.00018	-0.00003
	(0.2791)	(0.0005)	(0.0001)	(0.0003)	(0.0001)
1st Stage F-stat	251.29	42.48	42.48	42.48	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	22.416	0.875	0.024	0.059	0.001
Observations	20907	20746	20746	20746	19398
R^2	0.238	0.845	0.909	0.714	0.269

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.

to negatively affect not only own output but its quality as well.

4.3 Robustness Checks and Effect Heterogeneity

Workers in non-neighboring production units can hardly interact or observe each other. This specific feature of the production environment can be exploited to further validate 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

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, $\tilde{y}_{-i}$	0.01170 (0.0390)					
Non-neighboring Workers' Eggs per Hen, $\tilde{y}_{-i}$		-0.01822 (0.05726)				
Coworkers' Eggs per Hen, $\bar{y}_{-i}$			-1.48038*** (0.3688)	-0.28735*** (0.0661)	-0.47082*** (0.1671)	-0.32137*** (0.0631)
$food_{t-1}$	0.00409*** (0.0012)	0.00459*** (0.00123)	0.01250*** (0.0043)	0.00408*** (0.0012)	0.00438*** (0.0016)	0.00441*** (0.0012)
$food_{t-2}$	0.00274*** (0.0010)	0.00300*** (0.00081)	0.01131*** (0.0038)	0.00261*** (0.0010)	0.00153* (0.0008)	0.00394*** (0.0012)
$food_{t-3}$	0.00236** (0.0011)	0.00220*** (0.00081)	0.00964** (0.0040)	0.00217** (0.0011)	0.00061 (0.0009)	0.00444*** (0.0011)
1st Stage F-stat	21.65	85.03	251.29	29.61	31.60	193.21
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	19936	8294	20907	20907	10917	9980
R^2	0.925	0.888	0.899	0.927	0.9164	0.948

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 4.3. 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.

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 21.65. 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.[23]

Furthermore, the natural logarithm of the daily average number of eggs per hen collected can be replaced as outcome in the main specification.[24] 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 -1.48. 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 29.61. The estimated parameter of interest is highly significant and remarkably similar to the ones derived before.[25]

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.[26] 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

[23] 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.

[24] Such transformation is needed in order to match the conceptual framework proposed in Section 5. 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.

[25] 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.4 in the Appendix B.

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

separately and results reported in Columns 5 and 6 of Table 5. Estimated coefficients are negative and highly significant in both cases. Low and high ability workers seem thus to be equally responsive to changes in coworkers' productivity.

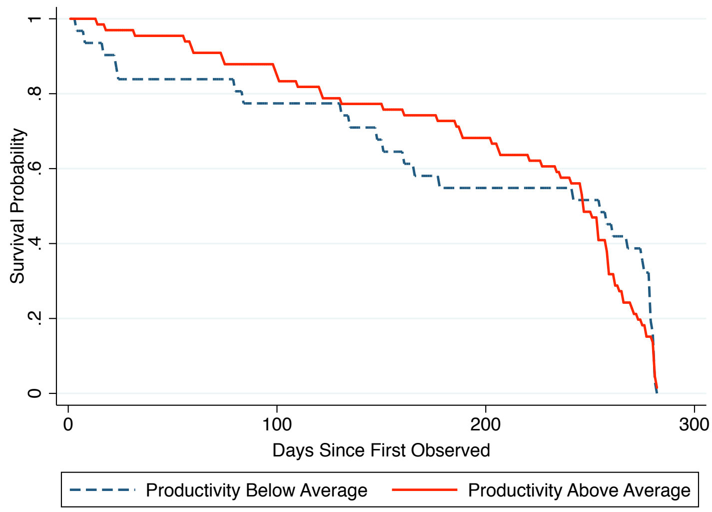
5 The Mechanism

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 to 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 26 terminations of employment relationship over a workforce of around 100 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.[27] 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).

Figure 5 plots the survival probability in the firm for the average worker over time, computed separately according to his initial productivity. The latter is measured as the daily number of eggs per hen collected by the worker on the first day on the job. Even eight months after the start, workers who are initially more productive than average are more likely to still be at work compared to those whose initial productivity is below the average. On top of this, our claim is that externalities exist among workers in their probability of keeping the job. Figure 6 provides preliminary evidence on this point. The figures show how the survival probabilities of a given worker relate with the initial productivity of coworkers in neighboring production units. The left and right figures are derived separately for workers whose initial productivity is respectively below and above the average. Conditionally on own productivity, the more productive coworkers initially are the higher is the probability for a given worker to keep his job. Furthermore, returns from being next to highly productive coworkers in terms of probability of keeping the job seem to be higher for those workers who are initially less productive.

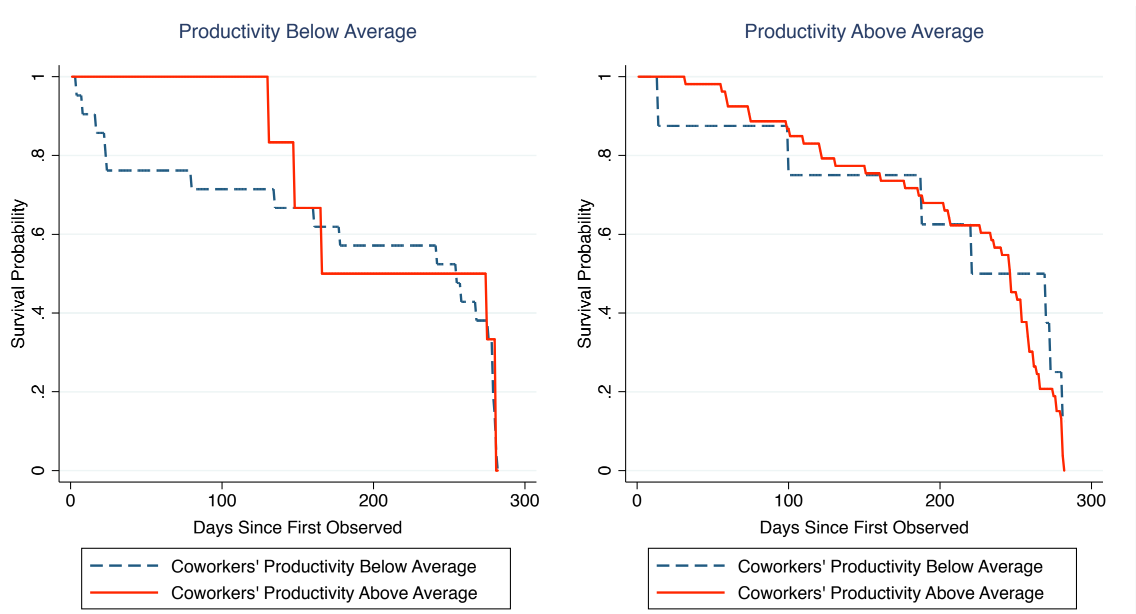
[27] See Section 6 and Table B.5 in Appendix B for more detailed information on the wage schedule of workers at the firm. Average and minimum wage data are from the World Bank.

FIGURE 5: SURVIVAL PROBABILITY AND PRODUCTIVITY



Notes. The figure plots the survival probability in the firm for the average worker over time throughout the sample period. The survival probability is computed separately for workers whose initial productivity (measured as daily average number of eggs per hen) is above and below the average productivity in the sample. Workers with higher initial productivity have higher survival probabilities.

FIGURE 6: SURVIVAL PROBABILITY AND COWORKERS' PRODUCTIVITY



Notes. The figures plot the survival probability in the firm for the average worker over time throughout the sample period. In the left figure the sample is restricted to workers whose initial productivity (measured as daily average number of eggs per hen) is below the average productivity in the sample. The survival probability is shown separately for workers whose neighboring coworkers have productivity above and below the average. The probability of survival is higher when coworkers' productivity is higher over most of the support. The right figure shows instead the corresponding figures for workers whose initial productivity is above the average. Again, their probability of survival is higher when coworkers' productivity is higher.

All this is true even five months after the start, and suggests that productivity at the shed level matters for worker evaluation and dismissal. We develop these arguments theoretically and validate them empirically in the remainder of this section.

5.1 Conceptual Framework

The main features of the production environment 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

$$y_i = f(e_i, s_i) \tag{2}$$

Effort and input quality are complement in production. In particular, let $f(e_i, s_i) = e_i s_i$. Input quality s_i can be thought of as a function of both observable and unobservable input characteristics. Effort is unobservable to the management, so that y_i is a signal of worker's exerted effort.[28]

As for now, 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. Unlike Mas and Moretti (2009), 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

$$\max_{e_i} U(\omega)\, q(y_i, \bar{y}_{-i}) - c\frac{e_i^2}{2} \tag{3}$$

Taking the corresponding first order condition yields

$$U(\omega)\, q_1(y_i, \bar{y}_{-i})\, s_i = ce_i \tag{4}$$

[28] 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.

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

$$\frac{\partial e_i^*}{\partial \bar{y}_{-i}} = \frac{U(\omega)\, q_{12}(y_i, \bar{y}_{-i})\, s_i}{c - U(\omega)\, q_{11}(y_i, \bar{y}_{-i})\, s_i^2} \tag{5}$$

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 may let an increase in coworkers' average output affect marginal returns from own output positively. Still under the assumptions of $q_1(\cdot) > 0$ and $q_{11} \leq 0$, this is the case if, for example, $Q_i = q\,(\alpha y_i - \beta \bar{y}_{-i})$ with $0 < \beta < \alpha$, which implies $q_{12}(\cdot) > 0$. In this case, the 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 $Q_i = q\,(y_i + (N-1)\bar{y}_{-i})$. This implies $q_{12}(\cdot) < 0$. The worker's optimal effort level will thus fall with an increase in coworkers' average output. In other words, 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.[29] 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.

[29]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 equilibrium exists.

5.2 Termination Policy: Empirics

Within the above conceptual framework, 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.[30] We already showed in Figure 6 how survival probability in the firm for a given worker is higher when coworkers' productivity is higher, consistent with the hypothesis that the management attaches to the latter a positive weight in the evaluation of individual workers.

We investigate these issues further through implementing a logistic hazard model and study the relative odds of the probability $1 - q(\cdot)$ of losing the job in period t as defined by

$$\frac{1-q(t)}{q(t)} = \frac{h(t)}{1-h(t)} = \exp\{\ \gamma_t + \alpha\, y_{it} + \beta\, \bar{y}_{-it} + \kappa\, y_{it} \times \bar{y}_{-it}\ \} \tag{6}$$

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.[31] 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 $\bar{y}_{-it}$,

[30] 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 $\eta_{es} = \frac{\partial e_i}{\partial s_i}\frac{s_i}{e_i} > -1$.

[31] 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.

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}	-6.598***	-8.287***	-13.322***	-8.489***	-11.505***	-15.983***
	(2.247)	(2.497)	(4.288)	(3.226)	(3.365)	(4.894)
$\bar{y}_{-it}$	-4.537***	-5.515***	-7.245***	-1.520	-2.574	-6.532***
	(1.615)	(1.736)	(1.785)	(1.498)	(1.583)	(2.371)
$y_{it} \times \bar{y}_{-it}$	8.277***	10.755***	14.126***	7.770**	11.449***	15.986***
	(2.597)	(2.736)	(4.932)	(3.501)	(3.533)	(5.500)
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	17981	17981	17981	15939	15939	15939

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. $\bar{y}_{it}$ 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 value 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).

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. Shed-level output thus seems to matter to some extent for individual termination probabilities. More importantly, the coefficient of the interaction term is positive and highly significant across specifications. 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.

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 holds when all information about individual productivity and input quality is sufficiently costly to process.[32] Limited managerial attention can then lead managers to process and rely positively on information about shed-level productivity in the evaluation of workers' performance (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. In both cases, positive teamwork-type externalities arise in the probability of keeping the job, leading to free riding among workers.

Finally, notice that some of the results from Section 4 allow us to rule out alternative explanations for the effect we find. Suppose that workers were to be monitored on the job by the management, that such monitoring efforts were 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 higher shirking which follows to a reallocation of monitoring efforts on behalf of the management. 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 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. The effect we find goes instead in the opposite direction.

6 Monetary and Social Incentives

Does incentive provision shape externalities in this context? Can sufficiently strong incentives offset the workers' tendency to free ride on each other and solve for the negative productivity spillovers as previously identified? Peer pressure mechanisms decrease the marginal cost of own effort, while monetary incentives increase its marginal returns. How does this affect how individual effort responds to changes in coworkers'

[32] 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.

productivity?

We first investigate these arguments in light of the suggested conceptual framework. 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' productivity $\bar{y}_{-i}$. Starting from the same framework presented above, the worker's problem becomes the one of choosing effort level $e_i \geq 0$ which maximizes the expected utility

$$\max_{e_i} U(\omega)\, q(y_i, \bar{y}_{-i}) - c\frac{e_i}{2}\,(e_i - \lambda\, \bar{y}_{-i}) \tag{7}$$

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.[33]

As for monetary incentives, their impact can also be incorporated in 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

$$\max_{e_i} (F + \kappa y_i) q(y_i, \bar{y}_{-i}) - c\frac{e_i^2}{2} \tag{8}$$

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 $q_{12}(\cdot)$.[34] 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

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

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

monetary incentives, as these are earned only if the job is kept. The latter effect may dominate the former, yielding positive productivity spillovers.

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

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

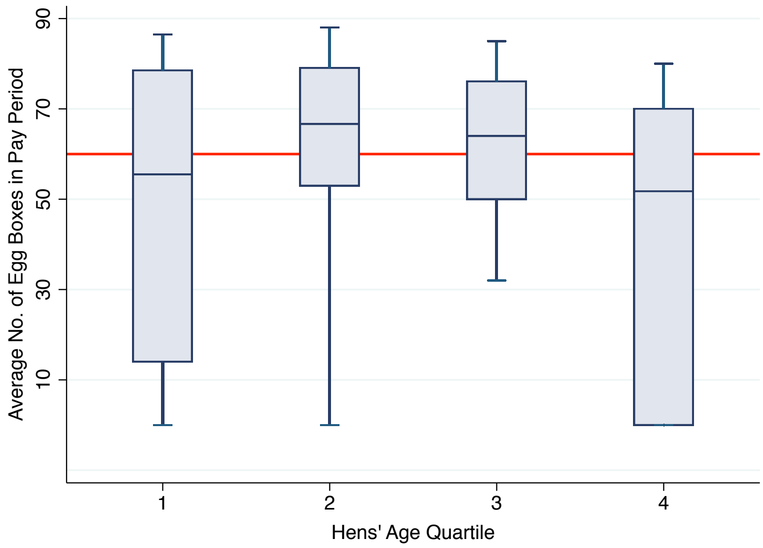
where ω is the base pay and Y_i is the amount of boxes of eggs collected by the worker in the randomly chosen day. This quantity is multiplied by 2 and, if the resulting quantity exceeds a given threshold r, a piece rate pay γ is awarded for each unit above the threshold. On top of base pay, almost all 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.[35]

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 7 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.[36]

[35] Table B.5 in 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).

[36] Table B.6 in 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'

FIGURE 7: 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.

In order to provide suggestive evidence on the role of monetary and social incentives, we explore effect heterogeneity through the following regression specification

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

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

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.

instruments for the endogenous interaction variables $\bar{y}_{-igwt} \times D_d$.[37]

We first focus on monetary incentives. As shown in Figure 7, 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, 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. 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. Consistently 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.

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, 24% 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.[38] Productivity spillovers are estimated to be negative and significant only for those workers who do not work along friends. Consistently with

[37] 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.

[38] 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.

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	-0.09785				
	(0.3148)				
$\bar{y}_{-i}$ × Low Productivity Age	-0.21834**				
	(0.1071)				
$\bar{y}_{-i}$ × Friend		0.22713			
		(0.1747)			
$\bar{y}_{-i}$ × No Friend		-0.43580**			
		(0.2104)			
$\bar{y}_{-i}$ × Experienced			-0.60567***		
			(0.1189)		
$\bar{y}_{-i}$ × Not Experienced			0.23650		
			(0.1587)		
$\bar{y}_{-i}$ × Low Age Difference				-0.13943	-0.38903
				(0.4793)	(0.3628)
$\bar{y}_{-i}$ × High Age Difference				-0.02430	-0.48440**
				(0.1338)	(0.2241)
$food_{t-1}$	0.00491***	0.00594***	0.00494**	0.00072***	0.00405***
	(0.0015)	(0.0019)	(0.0020)	(0.0003)	(0.0012)
$food_{t-2}$	0.00322**	0.00366**	0.00306**	-0.00010	0.00285***
	(0.0013)	(0.0016)	(0.0015)	(0.0001)	(0.0010)
$food_{t-3}$	0.00317**	0.00389**	0.00305**	-0.00027	0.00194*
	(0.0013)	(0.0016)	(0.0015)	(0.0002)	(0.0012)
1st Stage F-stat	17.16	32.39	21.36	5.45	4.90
	20.78	13.22	24.71	5.95	28.13
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	20907	16313	16313	10950	9950
R^2	0.902	0.915	0.935	0.839	0.933

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.

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 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.[39]

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 negative 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.[40]

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

[39]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.

[40]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.

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.

7 Counterfactual Policy Analysis

7.1 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 alternative 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 $\tilde{q}(\cdot)$.[41] 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% confi-

[41] We describe the full procedure to derive counterfactual productivity estimates in Appendix A.3.

TABLE 8: TERMINATION POLICY COUNTERFACTUAL: RESULTS

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

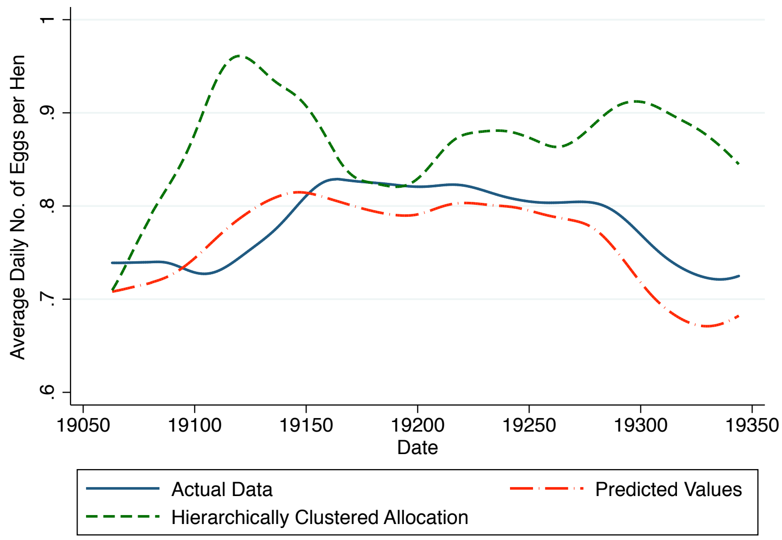
Notes. The Table shows productivity gains and losses from counterfactual termination policy as discussed and implemented in Section 7.2. 95% Confidence Intervals in square brackets, computed using bootstrapped samples from 200 repetitions. Productivity is measured as average daily number of eggs per hen over the period. Entries are percentage change with respect to actual data, with counterfactual productivity being derived using the corresponding parameter values.

dence intervals as computed by repeating the above estimation procedure 200 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%.

7.2 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. 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 generated in the system. Aggregate productivity will respond accordingly.

FIGURE 8: 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.

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 8 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 8. 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 0.0136 and significantly different from zero.[42] 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 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

[42]Figure B.2 in Appendix B shows the distribution of the average productivity difference across the 100 alternative scenarios.

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 analysis 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 additional aspects of human resource management practices in their interaction with production management. In this respect, our focus on production inputs and their allocation to working peers represents the main innovation with respect to the previous literature on the topic. What is also crucial for the external validity of our study is the absence of any technological externality among workers within the same organizational tier. This allows to isolate productivity spillovers of alternative origins. In a companion paper still work in progress, we aim at investigating 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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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

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

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 $\mathbb{E}\left\{f_i|\mathbf{v}\right\}$ 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

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

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, consistently 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 $g(a_i)$.

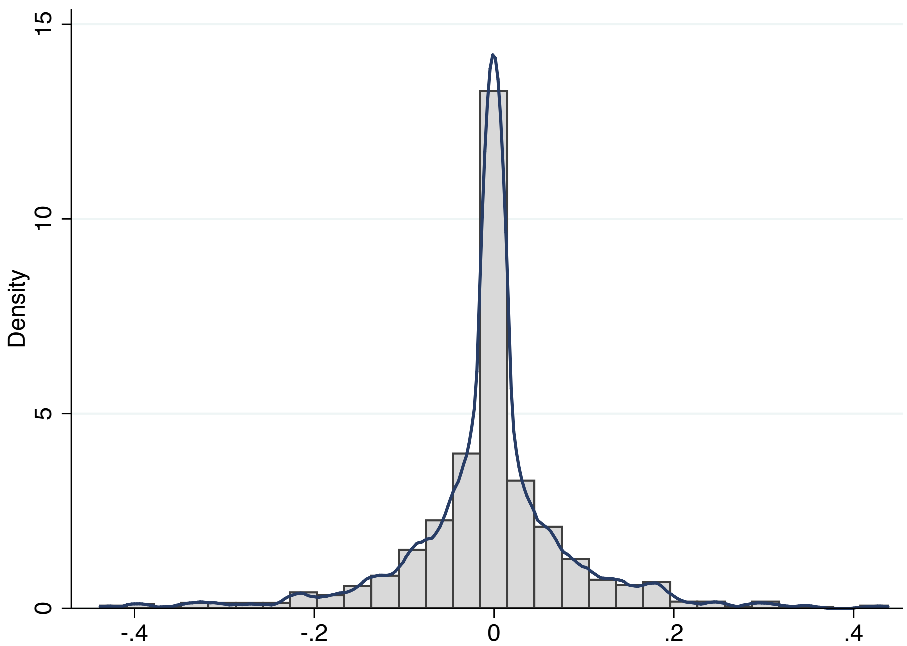
This is because, given the idiosyncratic unobservable component in input quality η_i, the principal cannot perfectly net out the input contribution to output. As a result, even observable increases in input quality increase the value of the signal the principal uses to calculate the expected level of 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 Section 6. 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.[43] 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'

[43] 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 Counterfactual Policy Analysis: Termination Policy

This section integrates Section 7.1 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.

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

$$\frac{U(\omega)}{c}\, q_1(y_i, \bar{y}_{-i})\, s_i = e_i \tag{14}$$

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

$$\ln y_i = \ln \frac{U(\omega)}{c} s_i^2 + \ln q_1(y_i, \bar{y}_{-i}) \tag{15}$$

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

$$\tilde{q}(y_{it}) = \alpha_0 + \alpha_1\, y_{it} + \alpha_2\, y_{it}^2 \tag{16}$$

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

$$\ln y_{it} = \ln \frac{U(\omega)}{c} s_{it}^2 + \ln(\alpha_1 + 2\alpha_2\, y_{it}) \tag{17}$$

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

$$\ln y_{it} = \ln U(\omega) + \ln s_{it}^2 + \ln \hat{q}_{1,it} - \ln c_i \tag{18}$$

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

$$\ln y_{it} = \alpha + \psi_{wi} + \beta \ \ln \hat{q}_{1,it} + \theta_i + \varepsilon_{it} \tag{19}$$

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

$$\widehat{\ln y_{it}} - \hat{\beta} \ \ln \hat{q}_{1,it} = \hat{\alpha} + \hat{\psi}_{wi} + \hat{\theta}_i = \hat{m}_{it} \tag{20}$$

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}

$$\ln y_{it} = \hat{m}_{it} + \ln(\alpha_1 + 2\alpha_2 \ y_{it}) \tag{21}$$

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

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)	(2)
Corr $(age_{igwt}, \overline{age}_{-igwt})$	0.8964	0.0067
p-value	(0.0000)	(0.5285)
Day FEs	Y	Y
Shed-Week FEs	N	Y
Observations	8745	8745

	Own Hens' Age, age_{igwt}
$\overline{age}_{-igwt}$	0.061
	(0.047)
$\overline{age}_{-igw}$	-0.397
	(0.399)
Day FEs	Y
Shed-Week FEs	Y
Observations	20907

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: OWN AND COWORKERS' HENS' AGE AND PRODUCTIVITY: ADDITIONAL RESULTS

	Daily Number of Eggs per Hen, y_i			
	(1)	(2)	(3)	(4)
age_i	0.03859***	0.03870***	0.03899***	0.03803***
	(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)
$\overline{age}_{-i}$		-0.00136***		-0.00387***
		(0.0005)		(0.0013)
$\overline{age}^2_{-i}$			-0.00001**	0.00003**
			(0.0000)	(0.0000)
$food_{t-1}$	0.00139***	0.00141***	0.00140***	0.00143***
	(0.0005)	(0.0005)	(0.0005)	(0.0004)
$food_{t-2}$	0.00079**	0.00082***	0.00082***	0.00082***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$food_{t-3}$	-0.00000	-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	0.857	0.858	0.858	0.858

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.4: BATCH REPLACEMENT AND FURTHER ROBUSTNESS CHECKS

	Daily Number of Eggs per Hen, y_i			
	(1) Non-replacement Weeks	(2) Replacement Weeks	(3)	(4)
Coworkers'	-0.31800***	-0.32766**	-0.18025*	-0.28353***
Eggs per Hen, $\bar{y}_{-i}$	(0.0737)	(0.1665)	(0.0968)	(0.0972)
age_i	0.02927***	-0.00683		
	(0.0070)	(0.1332)		
age_i^2	-0.00029***	-0.00027		
	(0.0001)	(0.0013)		
$food_{t-1}$	0.00440***	0.00037	0.00534***	0.00412***
	(0.0012)	(0.0017)	(0.0013)	(0.0012)
$food_{t-2}$	0.00260**	-0.00036	0.00415***	0.00249**
	(0.0011)	(0.0163)	(0.0016)	(0.0010)
$food_{t-3}$	0.00256**	0.02167	0.00391**	0.00219**
	(0.0011)	(0.0235)	(0.0012)	(0.0011)
1st Stage F-stat	16.43	30.81	119.72	76.13
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	Y	Y	Y	Y
Observations	20773	134	8726	20594
R^2	0.893	0.978	0.967	0.926

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 weeks with no replacement in the correspondent shed. Subsample in (2) contains observations belonging to weeks with any replacement in the correspondent 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 (3) and (4). $food_{t-s}$ are lags of amount of food distributed as measured by 50kg sacks employed.

Table B.5: Pay: Summary Statistics

Variable	N	Mean	St. Dev.	Min	Max
Base Pay (PEN)	1470	505.34	66.42	26	704
Bonus Pay (PEN)	1470	81.77	50.28	0	442
Total Pay (PEN)	1470	588.42	89.34	29	972

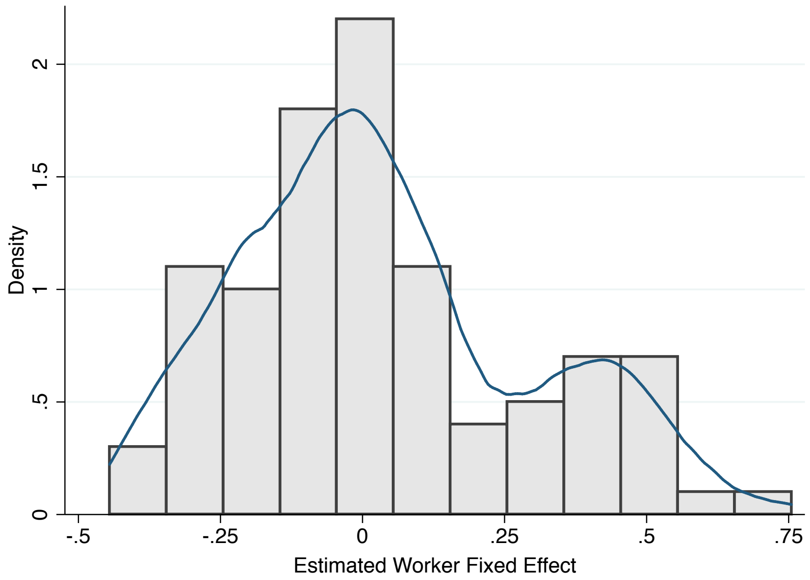
Notes. The Table reports summary statistics for the pay data. Workers are paid every two weeks. The wage formula is presented and discussed in Section 6 of the paper. The bonus component is calculated using the number of eggs boxes produced in a randomly chosen day within the same two weeks. 1 PEN = 0.38 USD (June 30, 2012), with minimum wage in the period being 750 PEN (285 USD).

Table B.6: Hens' Age and Bonus Pay

	Averages across Hens' Age Distribution			
	1st Quartile	*2nd Quartile*	*3rd Quartile*	*4th Quartile*
Base Pay (PEN)	509.43	519.84	522.09	515.20
Bonus Pay (PEN)	87.64	107.53	89.45	67.42
Total Pay (PEN)	598.77	625.61	612.93	583.72

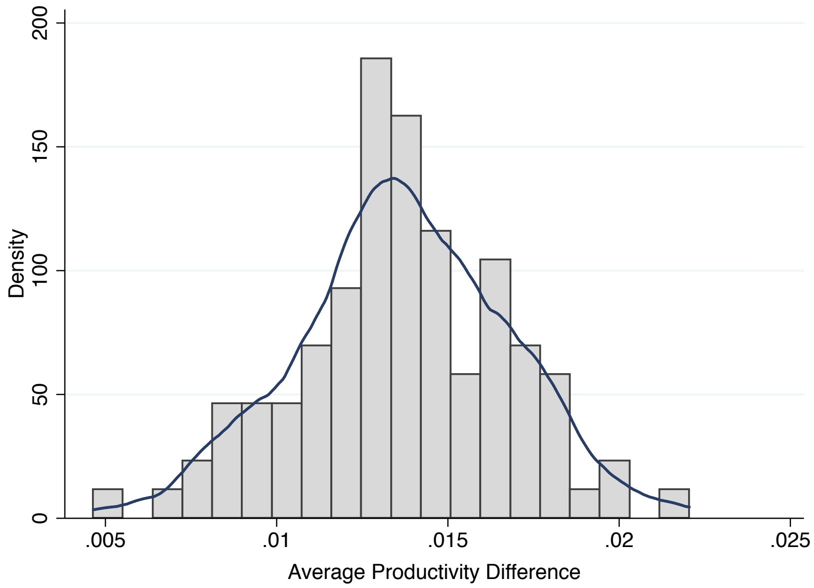
Notes. Average bonus pay per quartiles of hens' age distribution. 1 PEN = 0.38 USD (June 30, 2012).

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: 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 0.0136 and a standard deviation of 0.003. The average difference is thus significantly different from zero at the 5% level.