ESSAYS IN ORGANIZATIONAL ECONOMICS

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This thesis is dedicated to Alfredo, Elva, Pedro, Mercedes, Jose, Claudia, Cynthia and Ignacio, who give me a reason to smile everyday and never stop supporting me.

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Abstract

New managerial practices are not use on isolation. Managers use different organizational tools to maximize their firm's profits and they interact with the pre-established practices of the company. This dissertation analyzes some of these interactions, evaluating their performance and their effects on worker's behavior. The first chapter studies the allocation of decision-making rights on the firm when managers are able to choose her team composition in uncertain environments. The second chapter shows how input heterogeneity triggers productivity spillovers at the workplace and how social and monetary incentives affect the size and sign of spillovers. The third chapter studies the use of multiple performance measures on the design of incentive systems. There I study how the existence of performance threshold, the ratio of output/input prices and the workers risk aversion play an important role on the determination of the strength and the spread of the incentives.

Resumen

Nuevas prácticas administrativas no son usadas de manera aislada. Administradores usan diferentes herramientas organizacionales para maximizar las ganancias de sus empresas y éstas interactúan con la prácticas establecidas previamente por la empresa. Esta disertación analiza algunas de estas interacciones, evaluando su rendimiento y sus efectos sobre el comportamiento de los trabajadores. El primer capítulo estudia la asignación de derechos de decisión en la firma cuando los administradores pueden elegir la composición de sus equipos en contextos inciertos. El segundo capítulo muestra como la heterogeneidad de insumos produce externalidades productivas en el centro de trabajo y como incentivos monetarios y sociales afectan la magnitud y la dirección de estas externalidades. El tercer capítulo estudia el uso de múltiples medidas de rendimiento en el diseño de sistemas de incentivos. Además se analiza como la existencia de umbrales de rendimiento mínimo, el ratio de precios producto/insumo y la aversión al riesgo de los trabajadores juegan un rol importante en la determinación de la fuerza y la extensión de los incentivos.

Preface

The main objective of firms is to increment their profits. Shareholders demand managers' results in these terms and evaluate them accordingly. As a consequence, managers use all the tools available to pursue this goal. Those tools cover a large gamma of possibilities, e.g. organizational design, contract design, recruiting and firing policies. In the last decades have been impressive progresses on the study of each of those tools but most of the time in isolation. The theoretical analysis precedes the empirical studies given the difficulty to find appropriate data sets. The recent technological progress on the management of data sets, computing power and storage capacities facilitate the creation and access to new data bases for many researchers. At this point, researchers have realized that in real life situations, several management practices interact one with each other. It makes necessary to understand how different managerial and human resources practices affect the efficiency of firms, the communication among workers and the productive process.

This dissertation is a contribution on this direction. It covers a broad range of decisions taken by firms in real life situations, including, how managers allocate decision-making rights within their firms, peer effects among workers and the organization of the productive process, contract design and hiring. To address these questions, I use different empirical sources as laboratory experiments and field data. Our objective is to understand the managers' behavior, to point out any unintended effect and to identify the forces interacting with the different tools that could determine the firm's productivity.

The first chapter deals with situations where managers should jointly decide their team composition and the allocation of decision rights in the organization. We model the allocation of decision rights by a firm manager who must oversee the completion of tasks, but also must select her team composition. The optimal organizational structure is determined by the trade-off between the coordination conflict among workers and the managerial uncertainty over the nature of the tasks. Coordination conflict among workers is therefore endogenously defined by the manager's chosen team composition. We find that a manager prefers a decentralized organization (i.e. delegating decision rights to her workers) when uncertainty is sufficiently high. Moreover, for any level of uncertainty, the optimal team composition is always more heterogeneous in a decentralized organization than in a centralized one. In the laboratory experiment, we find that managers choose centralized organizations somewhat more often than predicted by the model, but correctly opt for more decentralization as uncertainty rises. Also, the experiment confirms that there are more heterogeneous teams chosen in decentralized organizations. However, the level of information does not have a direct impact on team heterogeneity, whereas it reacts to the evolution of the payoffs. Moreover, we find that managers react to negative outcomes by selecting disproportionately homogeneous teams. This chapter is a threefold contribution with the previous literature: 1) It provides empirical evidence for the relation between uncertainty and decentralization, 2) The model endogeneize the trade-off between information asymmetry and conflict of interest between workers and the manager through the selection of the team composition. 3) At the best of our knowledge, if the first paper studying a One-to-Many delegation problem in a laboratory.

The second chapter 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%. In terms of contribution, we are the first to focus on the role of inputs in the literature on human resource management and productivity; we are able to identify productivity spillovers at the workplace and how different variables affect their distribution across workers; and we find evidence on how social and monetary incentives affect size and sign of spillovers.

The third chapter studies the use of multiple performance measures on the design of incentive systems. I analyze the impact of a contractual change that takes place on the same egg production plant in Peru mentioned before. This firm offers me a natural multitasking environment where the manager has multiple measures of workers' performance to use on the final contract. In particular, the level of output (egg production) and input (food distributed). The output measure is more aligned to the objective of the firm but it is a noisier signal of the effort of the workers, while the input measure is more informative of the feeding effort of the workers but it is less aligned with the objectives of the firm. In our study, the firm moves from a contract using both measures to another one just using the level of output. I develop a stylized multitasking model with heterogeneous and limited liability agents. Then, I propose a simple methodology for the identification of the level of misalignment among different performance measures that jointly with this rich data set allow me to structurally estimate the parameters of interest from the previous model. Using these parameters, I find the a contract using both performance measures outperforms a contract using just on the most aligned measure ignoring the most informative one. The result is not surprising, but there are two different channels through the first type of contract dominates the second one and it will depend on the workers risk aversion parameter and the output/input prices. When workers are no to sensitive to the amount of risk they bear, the optimal linear contract will assign a negative piece rate to the input measure to minimize the cost of food. All the incentive on this case will be concentrated on a higher piece rate in the output measure. When workers are sensitive to the amount of risk they bear, the optimal linear contract assigned a positive piece rate to the input measure while reducing the piece rate assigned to the output measure that is noisier. In this way, firms reduce the risk premium they have to pay without reducing on the same magnitude the strength of the incentive provided. We also explain on detail the role of performance threshold on this type of linear contracts. Assuming a conservative workers' risk aversion parameter, I find a loss of efficiency of 2.5% on the daily profits produced per worker per day when the firm focus just on the most aligned measure ignoring the most informative one. This chapter provides us with one of the few empirical analysis understanding if firms and organizations use multiple performance measures appropriately.

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Chapter 1

OPTIMAL ORGANIZATIONAL STRUCTURE: AN EXPERIMENTAL STUDY

1.1 Introduction

A primary role of managers is to ensure an efficient allocation of tasks among workers.[1][2] This can be particularly difficult in rapidly evolving business environments, where managerial uncertainty about the nature of tasks may increase. One option for the manager is to opt for a decentralized organization that allows workers to allocate tasks among themselves, enabling rapid response to changing local conditions. However, successful coordination among workers or divisions must also be prioritized for the success of the firm. In particular, divisions with similar specializations may have a hard time deciding on how to divide tasks. For instance, the coordination problem among divisions inside Sony Corporation was a major reason behind its lost of leadership on the production of electronic devices. In 2012, intradivisional mis-coordination left Sony with a catalog of 30 different TV's, none of which could argue that they had the most

[1]This paper is coauthored with John Hamman from Florida State University.

[2]Marschak and Radner [29] underlined task allocation as an important issue in organizations and groups: *"We are seldom aware how inconvenient it would be if people would have their task assigned and reassigned at random, rather than in accordance with some principle of classification.[...] To answer such questions one has to compare the organizational cost of each kind of assignment, usually simultaneously with the comparison of gross payoffs, since these may also be affected by the choice."*

cutting-edge technology.[3] When coordination conflicts among workers or divisions reduce firm performance, the manager may prefer a centralized organization where she keeps control over all task allocation decisions. The trade-off between adaptability to uncertain business climates and across-division coordination, then, will play a critical role in a manager's assignment of decision rights in her firm.

Additionally, managers are often responsible for determining the makeup of their work group. Sometimes a specific skill is desired, but the added complexity in larger organizations may require a broader set of abilities. Firms spend significant resources on their hiring processes, with estimates ranging from two thousand dollars per worker (PwC 2013/2014 Human Capital Effectiveness Report) up to seventeen weeks' worth of wages for skilled labor (Blatter, Muehlemann and Schenker [8]). These costs are in addition to actual wages paid, and so in highly competitive markets the ability to hire good workers whose skill sets closely match a firm's need becomes paramount. The hiring decision, in determining the skill set of members of a work group, directly affects the intensity of the coordination conflict within the group. In other words, managers can reduce the coordination conflicts in a decentralized organization by choosing workers with more dissimilar specializations - more heterogeneous teams.

It is natural to think that managers use both tools - decision rights allocation and team composition - to cope with the uncertainty on their environments. We develop a simple model to capture several essential features of the interaction between these variables. The interaction between allocation of decision rights and team composition is potentially critical in managerial decision making. Despite the potential benefit for firms in modeling this decision environment, the interrelatedness of worker selection and allocation of decision rights has not been directly addressed in the academic literature. [4] This model studies a general type of coordination problem faced by firms - namely, the need to coordinate the efficient completion of multiple tasks. The model provides a conceptual framework to understand observed differences in organizational structures across firms in same industries or countries. We characterize the optimal combinations of team composition and allocation of decision rights under different levels of managerial uncertainty. We then test the main predictions of the model in a laboratory

[3] See the New York Times column *"How the Teach Parade Passed Sony By"* LINK

[4] Hart and Moore [25] and Dessein, Garicano and Gertner [13] do examine the optimal hierarchical positions of specialized agents (utilizing single assets) and coordinating (multi-asset) agents, with types exogenously determined.

experiment. The results show that while many subjects do make decisions that conform to the model's predictions, we see behavior that illustrates how difficult these decisions may be for firm managers outside the lab.

The key component in our model is the ability for the manager to select her team composition. This decision endogenously determines the degree of coordination conflict among workers in a task allocation framework.[5] In our model, the manager first determines whether to make the allocation decision herself after potentially learning the tasks (centralized organization) or to allow the workers to allocate tasks themselves (decentralized organization). Second, the manager decides which types of workers to hire. We consider a scenario in which the manager chooses among horizontally differentiated workers. In other words, managers choose the skill profiles she prefers to have in her organization. We can understand these profiles as different professions (e.g. Economist, Accountant, among others) or as different specializations across divisions (e.g. an R&D division and Product Development division). In this paper, managers choose their basic organizational design in situations where immediate re-structuring in response to a realized task profile would be problematic. Firms may change their allocation of decision rights and team composition, but those processes take time, making the initial team composition and organizational structure decisions very important. In other words, we cover situations where the time to respond to tasks is short and does not allow for fundamental changes in the components of the organizational structure.

We aim to capture a broad range of managerial decision-making by highlighting this connection between employee makeup and the allocation of decision rights within a firm. For instance, a research lab has to decide which types of engineers to hire before all of her projects are known or a hospital has to decide which type of doctors to staff in an emergency room without knowing what patients may arrive. But perhaps the best example is a consulting firm. In consulting firm, when a manager starts a hiring process she has already some type organizational structure well defined and she does not know the type of projects they will receive on future. Moreover, when they start a project they have to return an output to the client. The total cost of a project and the quality of the output will depend on tasks allocation among workers and how the workers

[5]Our emphasis on a task allocation framework is not meant to suggest that there are not other important types of coordination conflicts among workers. Certainly, workers beliefs, language, communication skills, personnel history, among others can affect workplace coordination.

capabilities fit the project requirements. Moreover, sudden changes on the workforce composition or in the organizational structure are expensive and time consuming. On these circumstances, the workers abilities the manager recruits are crucial to the firm's efficiency. The level of specialization of the workers will be critically affected by the organizational structure and the accuracy of information available to the manager. [6]

The main intuition behind the results can be captured with a simple illustration: A more heterogeneous or specialized team allows the manager to respond better to a more dissimilar task profile in a centralized organizational structure. However, if the task uncertainty is very high, the manager may not have enough information to properly allocate tasks, potentially leading to ex-post mistakes. To minimize the ex-ante impact of these mistakes, the manager prefers to choose a team around the most common task addressed by the firm. On the other hand, in a decentralized organization, workers have perfect information about tasks but a potential conflict of interest may arise between workers and manager. Workers with similar specializations may have difficulty agreeing on the efficient division of tasks. The manager can reduce the potential incentive conflict by selecting a more heterogeneous team in terms of specializations. However, the manager choosing an over-specialized team may fail to adequately address the most common tasks.

Comparing the manager's trade-off in the centralized organization and the potential conflict of interest appearing on the decentralized organization, we make clear predictions for both the type of workers hired and the allocation of decision rights as informational uncertainty changes. Two main predictions from the model are worth noting here; for high or moderate levels of informational uncertainty, decentralization is the manager's optimal allocation of decision rights. Also, the worker types should be more heterogeneous under decentralized decision-making than under centralized decision-making regardless of the level of uncertainty. Worker types will converge under centralization as uncertainty grows, but will be unaffected by this uncertainty in a decentralized structure.

[6] While the most direct connection deals with the type of workers hired to complete a range of unknown tasks, our model may also inform the organizational decision making process after a merger between different firms, divisions or branches. The decision of which workers to retain in the organization is closely related to the new potential projects or tasks given to the restructured firm. It is also possible that the merger process may cause the firm to change its organizational structure based on the makeup of existing divisions or employees. Some divisions may face more or less variation in task scope, suggesting a re-allocation of decision rights may be necessary for optimal function.

We test these predictions in a controlled laboratory experiment. We find that managers delegate decision rights more often as information uncertainty grows. At the best of our knowledge this is the first empirical evidence supporting this well-established theoretical result. However, we also find that there is a general tendency to choose a centralized structure more than is optimal. So, while the response to uncertainty is in line with the model's predictions, our data suggest that managers may retain allocation rights even in very low information conditions, which can be a costly decision. This is in line with recent experimental evidence that in delegation tasks, individuals exhibit preference to retain control at non-trivial costs to themselves. We also find that managers tend to select less specialized teams than those predicted by the model. However, they improve and get closer to the model predictions as they get more experienced during the game. Interestingly, we find a that team heterogeneity does not respond directly to the different levels of information but it significantly respond to the evolution of the payoffs per round. Moreover, we show that when managers observe that a worker's decision goes against their interest in previous rounds, they overreact, choosing a disproportionally homogeneous team in subsequent rounds. As uncertainty is reduced, this effect becomes more evident.

Our analysis is a first step in a broader research agenda attempting to understand the role of the team composition in relation to the allocation of decision rights. For instance, we want to analyze how the allocation of decision rights change when the manager has a given a pre-established team, when communication is allowed or when the manager has the option to pay a fixed cost to exert a veto power over her workers decision. Also, the allocation of decision rights may differ with the type of coordination problem. Empirical work examining these one-to-many delegation situations is currently lacking.[7]

The rest of the chapter is organized as follows: We discuss related literature more thoroughly in section 1.2 before developing our theoretical model in section 1.3. Our experimental design and specific hypotheses comprise section 1.4 and we discuss our results in section 1.5. Section 1.6 present some simulation of the model under some variants of the model and Section 1.7 concludes with general comments and discussion

[7] Brandts and Cooper [10] analyze the differences in performance in a centralized and decentralized organizations but they do not allow participants to choose. Weber [34] provides evidence of managers selecting the pace of growth of their teams in order to coordinate on a minimum effort game but there is no allocation of decision rights. Many other papers related to one-to-one delegation and the control premium are discussed on the literature review.

on future study.

1.2 Literature Review

Our study is related with different strands of the economic literature. Our main contribution is the incorporation of endogenous worker selection into the problem of the allocation of decision rights. Our experimental results also add to the recent studies examining the delegation tasks in an environment involving multiple heterogeneous agents.

Decision rights, coordination and adaptation: Recent theoretical literature in organizational economics studies the implications of modern property rights theory for the organizational structure within firms (e.g. Grossman and Hart [22], Hart and Moore [26]). Specifically, there has been a focus on how the allocation of decision rights affects a firm's ability to balance the trade-offs between what Williamson [35] called "coordinated growth" (suggesting a centralized organization) and rapid adaptation to local conditions, which favors a more decentralized organization as suggested by Hayek [27]. These papers, like ours, develop models of incomplete contracts to derive predictions for when firms may benefit from centralized or decentralized decision making. For example, several related articles study the tension in multi-divisional firms between task-specific managers and managers who coordinate multiple tasks (Dessein, Garicano and Gertner [13], Hart and Moore [25], Hart and Holmstrom [24]). These models develop conditions under which more or less autonomy between divisions is desirable, and also examine environments under which relationship-specific investment may lead to firms merging to overcome coordination failure.

Another closely related set of papers by Alonso, Dessein and Matouschek [3, 4] highlight the communication technology within a firm as central to the firm's organizational structure. Alonso, Dessein and Matouschek [3] expanded the Dessein [12] model of delegation in a cheap-talk game to include a central manager and two local managers. The central manager balances his lack of information on local conditions against the coordination conflict of the local managers when deciding between a centralized or decentralized organization. They showed that local managers will communicate better one with each other than with the central manager when coordination is very important. It leads to an optimal decentralized organization beyond the potential conflict among workers. Alonso, Dessein and Matouschek [4] analyze the opposite scenario. They show that there are also situations where a centralized organization allows for a better adaptation to a changing environment beyond the lack of information of the central manager. The key component of the model is the difference between the depth and breadth of the information. When the conflict among agents is not too strong, they send good information to the central manager and she can lead a coordinated adaptation.

Our model differs from those mentioned in several important ways. The primary distinction is that we endogenize the degree of coordination difficulty by allowing the central manager to select her workers. To focus on worker selection, we exogenously determine the central manager's degree of informational uncertainty. This uncertainty is endogenous (though ambiguous) in the two Alonso, Dessein and Matouschek [3, 4] models as well as in Dessein [12]. There are differences on the information in favor to the workers, which have the possibility to report it to their manager. However, the bias on the reported information would crucially depend on the importance of coordination and adaptation on the determination of the agent's payoffs.

There is also an experimental paper that examines the performance of different allocation of decision rights in a group decision-making environment. Brandts and Cooper [10] design a game to maximize the tension between coordination and distortion of information. A core result of the model in Alonso, Dessein and Matouschek [3] is that the coordination problem may easily be solved, highlighting the importance of the adaptability problem.[8] Brandts and Cooper [10] found that centralization strongly outperforms decentralization. The current study allows the degree of coordination tension to be endogenously determined by the managers' selection of workers, while also endogenizing the allocation of decision rights.[9]

Team Composition: The level of specialization of the team is another tool managers have available when facing uncertainty about their environment. This idea has also been considered previously on the economic literature. Becker and Murphy [7] show that a

[8] An important difference between Brandts and Cooper [10] and Alonso, Dessein and Matouschek [3] is that the former highlights the coordination problem between branches from both an ex-ante and ex-post perspective. In contrast, in Alonso, Dessein and Matouschek [3], the coordination problem between branches is high from an ex-ante perspective but not from an ex - post perspective. The latter makes decentralization a good option in the cases where coordination is really important.

[9] The empirical literature on the allocation of decisions rights among firms is rather scarce with a few exceptions. For instance, Bloom, Sadun and Van Reenen [9] shows that high-trust regions are significantly more likely to have a decentralized organization. While new data sets appears, laboratory experiments may help us to shed some lights to understand the allocation of decision rights across countries.

more specialized team increases productivity because each worker can spend more time in a specific task (increasing expertise), but it also increases the cost of coordination in teams. Mello and Ruckes [30] analyze the composition of a team with one manager and one worker. The heterogeneity in characteristics among them increases the access to different information but affects the willingness to exert effort when the manager chooses a project workers do not like. They conclude that an uninformed leader or a complete informed leader prefers a more homogeneous team. Van den Steen [33] analyzes the cost and benefits of homogeneity and the relation with the corporate culture of an organization. He states that in a world with different priors, homogeneity in beliefs and preferences facilitates delegation and coordination. The main trade-off in our paper differs from the trade-off analyze in these studies. We focus on how the level of heterogeneity of the team facilitates the allocation of tasks among workers.

Task Allocation: There are also some recent papers analyzing the relation between the organizational structure and the optimal task or resource allocation. Friebel and Raith [17] compare how centralized or decentralized organizations affect the allocation of monetary resources (capital) to different projects proposed by better informed division managers about their projects quality. However, their managers are ex-ante equal. Garicano [19] focuses on the importance of knowledge acquisition and the cost of communication as determinants of task allocation inside a firm. He proposes a hierarchical organization as the best way to assign the different tasks among workers when knowledge is an input in the production function. Unlike our model, Garicano [19] assume vertical differentiation among workers – some workers are more able than others. In a model with horizontal differentiation, Garicano and Santos [20] study how to match the tasks or projects with talent in a lawyer referral market. In this case, they focus on market solutions but not on organizational ones as those we use in this paper. Our paper is an attempt to explore the problem of the efficient matching between workers and task from another angle. We go inside the organization and avoid market solutions. We try to analyze different organizational solutions based in centralized or decentralized structures on the decision rights to exchange tasks in a horizontally differentiated team.

Delegation and the "Control Premium": Our project also fits nicely with the recent experimental and theoretical work on delegation. In the typical delegation models and experiments, delegation is studied in an environment where a principal may choose to transfer decision rights to an agent. This agent may have better information, but potentially misaligned incentives as well. In our model, we extend this by examining delegation from one agent to multiple agents, which introduces coordination as a new tension in addition to the informational asymmetry and misaligned incentives problem.

The rich theoretical literature on strategic delegation establishes many scenarios in which firm managers may optimize by ceding decision rights to a more well-informed agent, even in the face of incentive misalignment (Alonso and Matouschek [2], Hart and Holmstrom [24], Holmstrom [28], Aghion and Tirole [1]).Additional benefits have been revealed in recent experimental research. Hamman, Loewenstein and Weber [23] find that delegation enables principles to seek out a self-interested outcome at the expense of others without feeling responsible, taking actions via intermediaries they would never take directly. Furthermore, they find that delegation reduces the blame assigned to principals by those directly harmed by the self-interested action. Bartling and Fischbacher [6] and Coffman [11] measure responsibility in a similar environment by allowing the recipient or a third party to punish individuals for their actions. Both studies find significant reduction in punishment towards the principal when she delegates an unfair act. This result persists even if the intermediary has transparently no decision making ability (Oexl and Grossman [31], Drugov, Hamman and Serra [14]).

Other recent experimental studies have demonstrated that even in the face of beneficial delegation, many principals have difficulty in transferring their decision rights. For instance, Fehr, Herz and Wilkening [15] find that principals retain decision rights far too often and over-exert effort in a delegation game, exhibiting an "endowment effect" for authority. Similar newly released studies quantify this preference for authority - the "control premium" - in hierarchical relationships. Owens, Grossman and Fackler [32] find that individuals prefer to rely on their own performance in a quiz than another subject, even when their probabilistic earnings are much lower. Controlling for ambiguity aversion and overconfidence, among other factors, they find a control premium of $8-15\%$ of expected net assets. Bartling, Fehr and Herz [5] design a lottery selection game that allows them to quantify the degree to which individuals intrinsically value control of their decision rights. They find a control premium of around 16.7% that persists over a wide range of parameterizations.

The current project therefore fits nicely into the broad literature on decision rights in firms. We provide a test of the trade-off between adaptation and coordination in an environment that also enables us to identify the degree to which firm managers prefer to retain decision rights when it is not in their material best interest. We next discuss the theoretical model in more detail.

1.3 The Model

In this section, we adapt a Hotelling model with some key additions that enables us to make predictions regarding both the team makeup and the allocation of decision rights. We focus our attention in organizations comprised of three different members, a principal and two agents. The principal has a managerial role (manager) while agents have an operational one (workers). The workers are horizontally differentiated and we interpret those differences as diverse specializations among workers. The specialization of worker i is captured by θ_i and, at the beginning of the production process, each worker receives a task t_i^0. The specialization of the worker determines how costly it is for the worker to handle the tasks she receives.

The manager is able to choose the type of workers in her team. We assume she can perfectly observe the workers' specialization and that the labor pool covers the full range of tasks encountered in her business sector. Firms are often able to distinguish a potential employees skill set but it is more difficult to recognize ex ante a worker's productivity (vertical differentiation among workers). We abstract away from heterogeneous productivities and simplify the model by assuming that all tasks are completed at the end of the period. Thus, the total cost to the firm increases solely as the distance between the workers' abilities and their assigned tasks increase. The manager's objective is to minimize the total expected cost of the firm: $\mathbb{E}\sum_{i=1,2} C_i(t_i, \theta_i)$.

We assume that the specialization and the tasks have the same normalized support, $[0, 1]$. Ex ante the manager does not know the task assigned to each worker but she knows the distribution of tasks, $F(t_i^0)$. The task realizations for each worker are independent and identically distributed. For illustration, imagine the tasks on a linear structure in which the positions of the workers (θ_1, θ_2) have been selected by the manager and (t_1^0, t_2^0) are the tasks originally received by workers 1 and 2 respectively as in following figure:

A manager choosing the specialization of her workers under these assumptions would optimally select a homogeneous team where $\theta_1 = \theta_2 = E[t^0]$. $E[t^0]$ will minimize the maximum distance each worker can face and then the average expected dis-

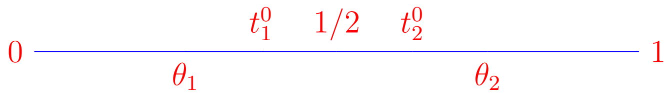


Figure 1.1: Linear Structure

tance experienced by each worker. Recall that the tasks are independent from each other and there are neither complementarities nor substituibility of the worker roles on the completion of their assigned tasks.

This somewhat trivial result becomes more interesting when we allow for task reallocation between workers. The assignment of decision rights for this reallocation will determine the optimal organizational structure of the team. We consider as centralized organizations those where the manager decides how to reallocate the tasks. A decentralized organization, then, is one in which the workers decide by unanimous vote whether or not to reallocate the tasks.

The organizational structure of the firm will play an important role in both team composition and firm outcome. Critically, the manager and workers have imperfectly aligned objective functions. We assume each worker receives a fixed payment that is high enough to cover her best outside option. As a consequence the worker focus on the minimization of her cost to do the task assigned. We consider t_i^0 as the original task realization of the worker i and t_i^1 as the final task assigned to the worker i. If the worker i has an specialization θ_i, then her objective is to minimize her cost function $C(\theta_i, t_i)$. In particular and for the rest of the paper we assume that $C(\theta_i, t_i) = |\theta_i - t_i^1|$. We can interpret the cost function as a measure of the difficulty that each worker has in completing a particular task given her specialization.

Information quality plays a critical role in the trade-off between organizational structures. In our model, the specialization of the workers is observed by both the workers and the manager. The differences in information come trough the observations of the realized tasks. We assume workers observe both tasks with certainty. Managers observe each task independently with some probability p. The probability p is known ex-ante by all agents. By varying the probability in the model, we capture the intuition that informational accuracy may differ across sectors or geographical locations.

The manager in our model will make two sequential decisions. First, she will determine the organizational structure in her team by retaining or delegating reallocation rights. After this, she must select the team composition that will maximize her payoffs given the structure selected. Unlike previous literature we want to understand how the possibility to select the team composition affects how the manager allocates the decision rights in the firm. It is natural to think that a manager has the option to select her own team when determining the best way to organize it.

The timing of the decisions in the complete model is divided in three stages as follows:

1. Stage 0: Organizational structure - The manager chooses either a centralized or decentralized organization. Remember that the distribution of the tasks and the probability p are known ex-ante by all the agents.

2. Stage 1: Team composition - The manager chooses the positions of her team members. Each worker receives a random task, t_i^0. The manager observes each task realization with an independent probability p and the workers observe both tasks with certainty.

3. Stage 2: Task Reallocation - The manager (centralized organization) or the team (decentralized organization) determines the final task assignment, t_i^1.

We find a unique sub-game perfect Nash equilibrium (SPNE) for this game using backward induction. We refer to the SPNE as the equilibrium for the rest of the document. First, we solve the manager's problem in a centralized organization and explain the main trade off the manager faces. Then, we solve the manager's problem in a decentralized organization and underline the main incentive conflict between the manager and the workers. Finally, we compare the two organizational structures to determine the manager's optimal organizational structure given the level of uncertainty.

1.3.1 Centralized organization and manager's trade off

Our purpose in this section is to identify the manager's optimal team selection in a centralized organization. Recall that a manager may see one realized task, both tasks, or neither task, depending on the independent probability p. We assume managers respond to these different situations following a behavioral rule:

- If the leader observes both tasks, she reallocates tasks minimizing $\sum_{i=1,2} C_i(t_i, \theta_i)$

- If the leader observes only one task, she would assign the task she observes to the worker with the closest position.[10]

- If the leader does not observe any message, she maintains the status quo (no exchange)[11].

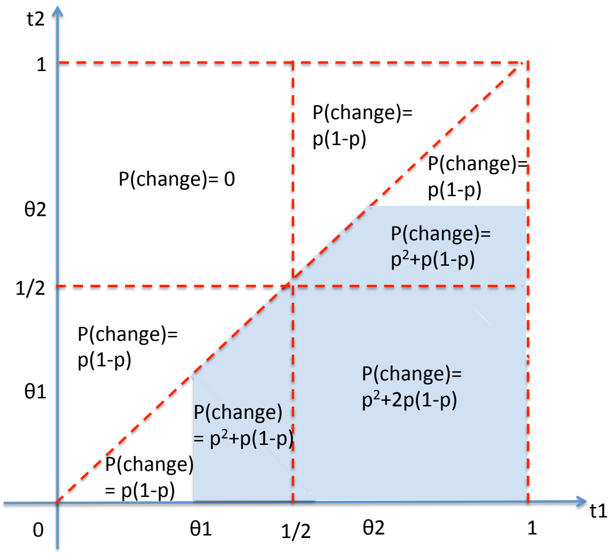


Figure 1.2: Centralized organization: Managers' probability to reallocate tasks

Figure 1.2 considers the probability that the manager decides to reallocate tasks for each realization of the state of the world, (t_1^0, t_2^0). The shaded area represents the region where the manager would like to exchange tasks under perfect information. Since the manager does not always observe both tasks, she is likely to make some errors *ex post* in task reallocation. Two types of errors appear as a consequence of the established rule. The manager may fail to exchange tasks in a region where she would have preferred to do so (Type I error), and she could exchange tasks with some probability in the region

[10]This behavior is consistent with minimization of the expected cost comparing both organizational structures. At the same time this behavior is supported by the data we obtained in the experiment. 75% of the rounds where the manager observe one task, she follows this behavior.

[11]If the leader decides to follow a mixed strategy where she exchanges tasks half of the time, the results would be the same.

where she would prefer not to change *ex post* (Type II error). In Figure 1.2, we identify the manager's reallocation of tasks as a function of p for all the possible states of the world, (t_1, t_2) given θ_1 and θ_2.

This probability influences the final worker positions the manager chooses. We have already mentioned that when the manager has no chance to reallocate tasks, she will position the workers in $\theta_1 = \theta_2 = E[t^0]$. However, the same is true when the manager has the possibility to reallocate tasks and $p = 0$. In other words, $\theta_1^*(p = 0) = \theta_2^*(p = 0) = E[t^0]$.

On the other extreme, when there are reallocation possibilities and $p = 1$, the manager would not choose the same positions for both workers. If the team is homogeneous, reallocation can not change the final outcome experienced by the firm. If the firm wants to take advantage of reallocation possibilities, the manager must select a more heterogeneous team. In particular, if we assume the distribution of each task is uniform, the optimal positions tend to $\theta_1 \approx 0.29$ and $\theta_2 \approx 0.71$.[12]. Let $\delta(\theta_1, \theta_2) = \frac{\theta_2 - \theta_1}{2}$ be defined as the measure of heterogeneity of the team selected by the manager.[13]

Proposition 1. *If tasks have a uniform distribution with support* $[0, 1]$*, there exists a unique optimal decision* $(\theta_1^*(p), \theta_2^*(p))$ *for the cost minimization problem of the manager in a centralized organization. The solution has the following characteristics:*[14]

1. *The optimal positions are symmetric with respect to* $E[t^0]$.

2. *The optimal positions imply team heterogeneity,* $\delta(p) > 0$ *if* $p \neq 0$.

3. $\delta(p)$ *is a monotonic function of* p.

Intuitively, the symmetry around the expected task realization is natural since we assume a symmetric distribution and a worker's action on one side of the mean is a mirror of a equidistant worker's action on the other side. As expected, the manager prefers

[12]Intuitively, one can expect the solution to be closer to the values 0.25 and 0.75. However, remember that the state of the world for the manager has two dimensions depending on each task. This state of the world follows a joint distribution formed by two identical and independent uniform distributions in our example.

[13]Notice $\delta(\theta_1, \theta_2) \in [0, \frac{1}{2}]$. The division by two is only for numerical tractability and it does not affect any of the results. Moreover, if we assume symmetry of the worker positions relative to the ex-ante expected task, we get: $\delta(\theta_1, \theta_2) = E[t^0] - \theta_1 = \theta_2 - E[t^0]$.

[14]Proof in Appendix A.1.

a more heterogeneous team if she expects to successfully coordinate the reallocation of tasks. A poor information environment, though, increases the probability that the manager makes bad decisions. As a consequence, the manager will choose a more homogeneous group to minimize the impact of misinformation. In any case, notice that an overly-homogeneous team reduces the benefits of task reallocation. In a firm setting, if the information environment depends on manager expertise, our proposition states that an inexpert manager would prefer a more homogeneous team than an expert one in a centralized organization.

1.3.2 Decentralized organization and incentive conflict

The manager's objective is unchanged in the decentralized organization. She must choose a team composition to minimize the expected distance between workers and tasks. However, the workers now decide whether to reallocate the tasks. On one side, it has the potential to improve the reallocation of tasks because the workers are better informed. On the other side, the workers' preferences are not perfectly aligned with the manager's preferences. Because unanimity is required to reallocate tasks, either worker can unilaterally guarantee the status quo task assignment. We can therefore identify instances where the manager would like to exchange the tasks but one of the workers do not. These are displayed in Figure 1.3.

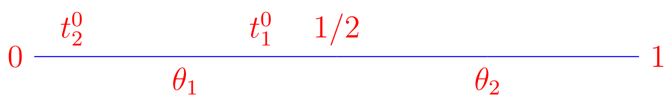


Figure 1.3: Main Incentive Problem

Workers in positions θ_1 and θ_2 originally receive the tasks t_1^0 and t_2^0 respectively. Worker θ_1 minimizes her cost with her assigned task and will vote to not switch. As a result no exchange takes place, though both other group members would have preferred reallocation. The reallocation of tasks in this case also maximizes the joint profits for the entire group. We could implement a market mechanism to correct for the inefficiency. However, we save the possibility of coasian bargaining for later study in order to focus on the organizational decisions of the manager.

Assumption 2. *There is no monetary transfer among workers.*[15]

In the following graph we focus on symmetric positions equidistant to the $E[t^0]$ and we assume without loss of generality that $\theta_2 > \theta_1$. Both conditions are satisfied in equilibrium. The domain of (t_1^0, t_2^0) represents all possible states of the world. Figure 1.4 highlights two symmetric areas where the manager would like to exchange tasks and one of the workers does not. The striped triangle on the bottom left is the area where the worker in position θ_1 does not want to exchange tasks. The striped triangle in the top right is the area where the worker in position θ_2 does not want to exchange tasks. Those areas are the graphical representation of the potential incentive conflict between the managers and the workers in a decentralized organization. The shaded area considers the cases in which both workers decide to reallocate tasks on the (t_1^0, t_2^0) plane. In Appendix A.1, we explain how we identify those cases. The shaded area plus the two triangular areas pointed out previously plots the cases where a manager with perfect information $(p = 1)$ decides to reallocate tasks.

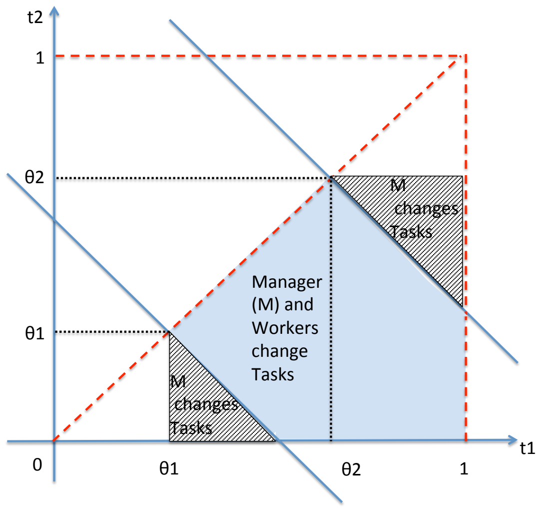


Figure 1.4: Tasks' reallocation regions.

The previous graphical exercise takes θ_1 and θ_2 as given. The two blue diagonals

[15]In the task reallocation settings inside firms, Garicano and Santos [20] or Fuchs and Garicano [18] study market solutions in order to get the most efficient matching between workers and tasks. We want to focus in organizational solutions to that problem. We focus in cases where monetary transfers between members of the team are unlikely. For instance, when those transfers have a reputational cost.

in Figure 1.4 determining the area where the workers reallocate tasks are parallel and they cross the 45 degree line exactly on the positions selected by the manager. If we assume that the manager chooses a more homogeneous team, those parallel lines get closer and the areas representing the incentive conflict grow larger. On the contrary, if the manager chooses a more heterogeneous team, those parallel lines get farther apart and the areas representing the incentive conflict get smaller. However, notice that on the extreme, with a perfectly heterogeneous or homogeneous teams there is no conflict at all.

Definition 3. *A measure of the incentive conflict between the manager and the workers would be:*

$$I(\delta) = \begin{cases} Pr[(t_1, t_2) \in T^M] - Pr[(t_1, t_2) \in T^W] & \textit{if } \delta \in [0, \frac{1}{2}) \\ 0 & \textit{otherwise} \end{cases}$$

where $T^M = ((t_1, t_2)|$*manager strictly prefers to exchange tasks when p=1 given* θ_1 *and* $\theta_2)$ *and* $T^W(\theta_1, \theta_2) = ((t_1, t_2)|$*workers exchange tasks given* θ_1 *and* θ_2 *by unanimity*$)$.

The difference between the probability of exchange tasks from the manager's perspective under perfect information and the probability to exchange tasks for the team is our measure of the incentive conflict. It is always positive since $T^W \subset T^L$. Then, we can state:

Proposition 4. *Under uniform distributions of the tasks,*

- $I'(\delta) \leq 0$
- $\lim_{\delta -> 1/2} I(\delta) = 0$ *and* $\lim_{\delta -> 0} I(\delta) = 1/4$

In the decentralized organization, the manager has to choose the positions of her workers minimizing the incentives conflict and maximizing the benefits of the tasks reallocation. In Appendix A.1 we prove the manager's optimal solution in the decentralized organization:

Proposition 5. *If we assume that each worker's task follows a uniform distribution on the interval* $[0, 1]$*, we obtain that:*

- *The optimal positions are symmetric with respect to* $E[t^0]$.

- *The optimal positions implies the same team heterogeneity for all p.*
- *The manager chooses a more heterogeneous team in a decentralized organization than in a centralized organization for all p.*

$$\delta^D(p) = \frac{1}{2} - \theta_1^D(p) > \frac{1}{2} - \theta_1^*(p) = \delta^*(p) \; \forall \, p \; \in \; [0,1]$$

Since the manager wants to reduce the incentive conflict, she chooses a more heterogeneous team than in the centralized organization. As a result, the members of the team exchange tasks more often. In other words, the manager contracts less homogeneous workers when she can not reallocate the tasks between them. Also, since the manager affects the final results of the workers only through the positions selected, the optimal positions are independent of the level of information p. Our result in this way differs from the result in Van den Steen [33]. That model states that the homogeneity in beliefs and preferences of the workers inside the team facilitate the communication and coordination among them. But, it does not consider the possibility to reallocate tasks. The nature of the problem and the necessity of unanimous agreement from both workers are the sources of our proposition.

1.3.3 Optimal organizational structure

In sections 1.3.1 and 1.3.2 we have the optimal positions selected by the manager given the actions of the workers in each organizational structure. Now, we compare both solutions in order to determine which organizational structure the manager prefers. The main parameter affecting the manager decision is the level of information:

Proposition 6. *When the tasks have a uniform distribution, there exists an informational accuracy p^* such that:*

- *If $p \geq p^*$, the manager prefers a centralized organization.*
- *If $p < p^*$, the manager prefers a decentralized organization.*

Proposition 6 states that the manager prefers to have the right to reallocate tasks among her workers when the level of information is good enough. On the other hand, when the manager's information is poor, she prefers to delegate task reallocation rights to the workers. Under this condition, the manager takes advantage of the workers' superior information and reduces the incentive conflict to minimize reallocation mistakes. This result is not surprising and has been pointed out before in the literature. For instance, Dessein [12] shows that a manager would prefer to delegate the decision rights to a more informed agent as long as the incentive conflict between them is not too large with respect to the principal's uncertainty about the environment. That model assumes an exogenous bias between the preferences of the manager and the workers which impacts in the strategic communication between them. We depart from Dessein by endogenizing the incentive conflict between agents, which is determined by the manager when she chooses team composition.

1.3.4 Theoretical predictions

The trade-off emphasized on the model allows us to make a series of predictions that we tested using a controlled laboratory experiment. In doing so, we aim to test the model's tension between the coordination problem among workers and the need for the team to respond effectively to tasks.

The experiment is described in detail in the next section, but a basic understanding is needed for our predictions. Each subject will play three distinct blocks of several rounds each. The first two allow the manager to familiarize herself with team selection in a centralized or decentralized environment, after which she enters a third block in which she decides both the team composition and now the organizational structure as well. This provides a stronger test of the model by giving subjects experience and feedback in both organizational structures before they must choose the organizational structure themselves.

In the experiment we consider a uniform distribution of the tasks over the support $[0, 100]$. Under these assumptions the value of p^* predicted by the model is approximately 0.82. At this value, the participant in the role of the manager is indifferent between the two types of organization. For values above 0.82, the manager prefers a centralized organization; and for values below, the manager prefers a decentralized organization. For this reason, we chose three different treatments, each capturing a different level of information accuracy. In the experiment, the probability p took one of the following values $[0.2, 0.5, 0.8]$. First, we do not choose a value of 1 because it implies perfect information for the manager. The decision of a manager with perfect information is always a centralized organization. This information would not reveal anything respect to the organizational preferences of the participants. We do not consider 0.9 as a relevant treatment because this value is too close to 1. Again, the body of experimental work on the control premium (among other topics) demonstrates that people are much more likely to sub optimally retain control than to sub optimally cede control. Thus, our design allows us to examine the behavior of subjects as they approach the information threshold but in environments that call for decentralization. By symmetry, we decide to have the treatment 0.2 and for completeness we include the treatment 0.5. Then, our first prediction is:

Prediction 1. *In all treatments, the manager will delegate decision rights to the workers.*

The predictions of the model with respect to the manager's choice of the optimal team composition are the following: In a centralized organization, the manager should select the positions around $(42, 58)$ in the 20% treatment, positions $(35, 65)$ in the 50% treatment and positions $(29, 71)$ in the 80% treatment. In a decentralized organization, the manager should select the position of $(27, 73)$ in all the treatments independently of the level of information. The predictions with respect to the optimal team composition are therefore:

Prediction 2. *Team composition in a decentralized organization is always more heterogeneous than in a centralized organization for any level of information.*

Prediction 3. *In a centralized organization, the heterogeneity of the team increases when the accuracy of the manager's information increases.*

Prediction 4. *In a decentralized organization, the team composition is independent of the accuracy of the manager's information.*

1.4 Experimental Design

We conducted this experiment in two locations. Initial sessions were run in the LEEX lab at Universitat Pompeau Fabra, and a second round of sessions were run in the xs/fs lab at Florida State University. Subjects were recruited using ORSEE (Greiner [21]) at

FSU and all sessions were run using the zTree software (Fischbacher [16]). FSU sessions consisted of 24 subjects, and each subject received a \$10 show-up fee in addition to money accumulated from the game. UPF sessions had 21 or 24 subjects, with each receiving a €5 show-up fee. Sessions lasted just under two hours and average earnings were approximately €16 (\$22) and \$24 in Spain and the U.S., respectively.

We implement a hybrid between/within design where the probability of the Central Manager seeing each task was fixed within a session at $p \in [0.2, 0.5, 0.8]$. The session was broken into three blocks. Blocks 1 and 2 were either Centralized or Decentralized (counterbalanced for each value of p), and block 3 was a Selector stage, described in detail shortly. Instructions were first read aloud that included the value of p for the session (translated to Spanish for UPF by a native speaker also fluent in English – see Appendix A.2 for instructions and screenshots), after which subjects were randomly assigned a role of Manager (M), Worker 1 (W_1), or Worker 2 (W_2) in three-person groups. Roles were denoted Participant A, Participant B1, and Participant B2. Subjects were only read instructions for each block as it was reached, though they knew there would be three blocks from the beginning. They were also reminded (before block 1 and each subsequent block) that they would play in the same role and face the same value of p for all blocks.

Blocks 1 and 2 lasted 10 rounds each. It was announced that groups would be fixed for each block with random rematching between blocks. Figure 1.5 shows the general time-line of each round for all blocks. At the beginning of each round, M chooses the type of workers W_1 and W_2 by assigning each a "placement" between 0 and 100. During the instructions, all subjects were given the chance to familiarize themselves with this task using the exact same screen they would see during the experiment (see appendix A.2). The M may enter any number of different values before finalizing her choice. Once the placement decision was made, the positions of W_1 and W_2 were fixed for the remainder of the round.

Once W_1 and W_2 had been placed, the position of the tasks assigned to each worker were revealed. Workers saw both task positions with certainty, and were told which task had been matched to them. M saw each task position independently with the probability p for that session. Once the tasks were revealed or not to all group members, subjects completed a "switch" task. This task determined whether the workers would switch

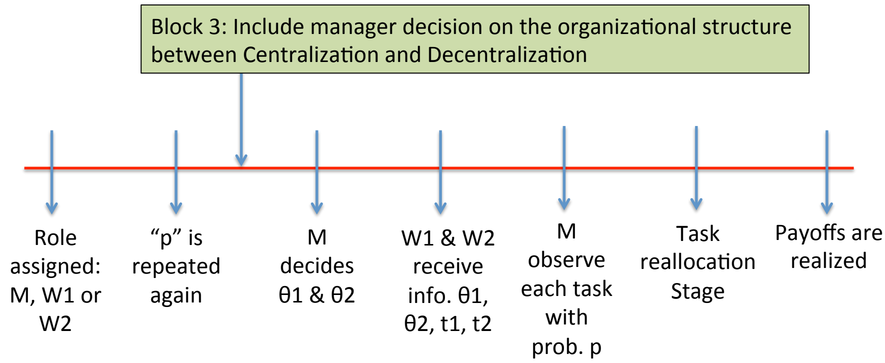


Figure 1.5: Single period timeline

tasks or not. Subjects knew that workers and tasks could not be repositioned between 0 and 100, they could only switch which task was assigned to which worker. In the Centralized environment, the M made the switch decision unilaterally, whether she saw one, both, or neither task position. In the Decentralized environment, workers voted over whether to switch. Only an unanimous vote to switch would result in a switch. If only one worker voted to switch, the tasks remained as initially assigned.

Payoffs for group members were determined as shown in the equations below. It was possible, though improbable, for subjects to earn negative payoffs in a round. To minimize this risk, subjects received their total earnings collected over all rounds of the session and were reminded of this fact.

$$\pi_{W_i} = 50 - |T_i - W_i|$$
$$\pi_M = 50 - 0.5 \sum_i |T_i - W_i|$$

Where task T_i is matched with worker W_i at the end of the round. These formulas were explained to subjects with several examples, and subjects were given a calculation screen during the instructions with which to familiarize themselves with the payoffs (see appendix B). The experimenter walked through an example at this time, with and without switching tasks. Once all subjects had some time to experiment with the payoff calculator, the experimenter made the following scripted comments to help ensure subjects knew how their decisions affected their payoffs: "What these payoff functions tell you is simply that you maximize your payoffs when you minimize the distance between each B participant and that participant's final marker. Note also that the A participant increases his or her payoff by minimizing the distance between each B participant and that participant's marker. Nothing in the payoff function depends on the B participants being close to each other or far apart from each other."

Once subjects completed both the placement and switch tasks, results were displayed providing them with information about their decisions in that round and their payoffs. In the Centralized rounds, workers were informed of their final assigned task, task positions, whether the M switched tasks, and the payoffs of all group members. Each M was reminded of any task position revealed to her, but workers did not see which task positions had been revealed to the M. In the Decentralized rounds, the M was notified whether or not the workers chose to switch tasks; otherwise the information revealed was the same.

Once blocks 1 and 2 concluded, subjects were read instructions for block 3, which we refer to as the Selector stage. Block 3 consisted of 16 rounds that were identical to blocks 1 and 2 with one addition. Prior to making the placement decision, the M made a new decision to begin each round of block 3 that determined whether that round would be played in the Centralized or Decentralized environment. Specifically, the M selected whether herself or the workers would complete the switch task for the round. Once the M made this choice, she completed the placement decision and the round then mimicked either a round from block 1 or a round from block 2.

1.5 Experimental Results

The analyses are structured to directly address the predictions from section 1.3.4. We divide the predictions of the model in two groups. We begin with an examination of a manager's organizational structure decisions. Specifically, how are decision rights allocated under different levels of informational accuracy? The Selector stage allows us to classify managers into one of three types based on their allocation of decision rights in each period - that is, their willingness to decentralize. We then look closely at team selection. Within each organizational structure, how effectively do managers vary their team composition to optimize responses to task realization? We then analyze the results to managers and workers by examining in-game payoffs.[16]

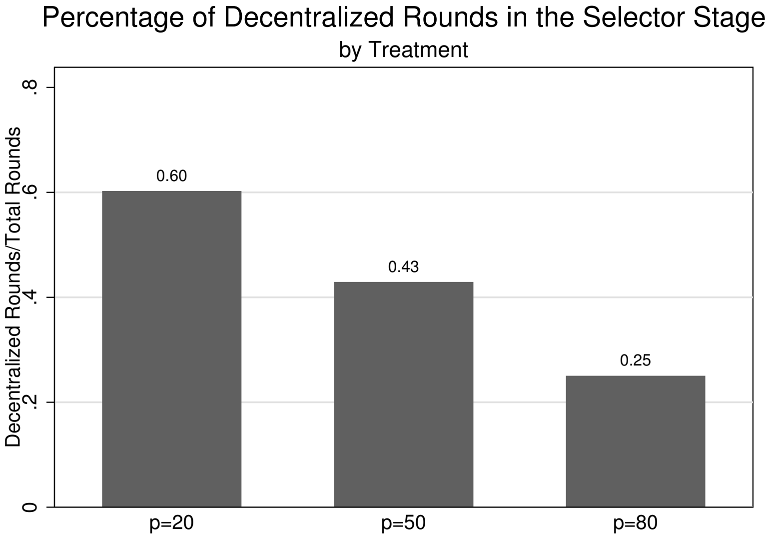
1.5.1 Organizational Structure Decisions

Our first prediction was that managers would choose a decentralized structure during the Selector stage in all information conditions, since the threshold for centralized control (information probability of 0.82) is above our most accurate treatment. Recall that after playing ten rounds each in a centralized and decentralized structure, managers in this third stage decided at the beginning of each round if they wanted to play in a centralized or a decentralized organization, making sixteen decisions in total.

Figure 1.6 plots the percentage of rounds in which managers decided to decentralize in the Selector stage by information accuracy. The managers decentralize more than sixty percent of the time in the 20% treatment (289 of 480 rounds). This drops to 25% in the 80% treatment (120 of 480 rounds). The different proportions between treatments are significantly different (Pearson's chi-squared = 121.61; p=0.000). There are two things to note: Not all of the rounds were decentralized, contrary to the model's first prediction. However, the number of decentralized rounds increases as the accuracy of information decreases, as predicted by the model. The simulation results help explain this behavior.

Aside from the fact that the participants do not decentralized in all rounds, they do so significantly more often when facing poorer information. In the model, the expected difference in performance between the decentralized and the centralized organizations - when the managers choose the optimal team composition - reduces as the level of information increases. This is due to worse performance by managers in task reallocation when the information is poor. Because workers have complete information, the expected payoffs in the decentralized game are not affected by the level of information.

[16]Our main theoretical predictions rely on some behavioral assumptions that we can verify with our experimental data. In particular, we are able to check the switching decision of the agents to evaluate the consistency of the assumptions made in the model. The type A participants (Managers) observed both markers on 30% of the cases on the experiment, they made mistakes on their switching decisions in only 6% of the cases. This percentage reduces to 3% in the selector stage. Also, managers observed at least one of the markers in 41% of the centralized rounds. They assigned the observed marker to the worker with the closer position in 75% of the cases. In the decentralized rounds, the switching decision was made by the B participants (Workers) via unanimous voting. The B participants deviated from predicted switches in just 6% of the cases. The vast majority of these cases occur when workers vote to not switch when switching would be profitable ("sins of omission").



Notes. The figure plots the percentage of rounds that the A participants decided to decentralize in the "Selector" stage. We had 30 A participants in the 20% and 80% treatments and 29 A participants in the 50% treatment, 480 and 464 rounds respectively.

Figure 1.6: Percentage of Decentralized Rounds in the Selector Stage

As we show in the next section, the managers do not select on average the team composition predicted by the model. However, the evidence strongly suggests that they have a harder time in the centralized organization with lower levels of information than in the decentralized organization.

To further support the pattern in Figure 1.6, we implement the following regression specification to control for additional factors:

$$y_{ir} = \alpha + \delta_r + \beta_1 Treatment(p = 50)_i + \beta_2 Treatment(p = 80)_i + \gamma X_i + u_{ir}$$

where y_{ir} is a dummy variable for the decision of the organizational structure: this variable takes the value 1 if the manager i chooses to decentralize in round r and 0 otherwise. δ_r is a set of dummies capturing overall trends in rounds and $Treatment(p = 50)_i$ and $Treatment(p = 80)_i$ are treatment dummies. Finally, X_i are participant controls and u_{ir} captures residual idiosyncratic determinants by participant i in round r. We are not considering participant fixed effects in our specification because our main concern is the between effect and not the within participant effect. Moreover, the main purpose of our experimental design was to randomized participant's unobserved characteristics across sessions. Our main identifying assumption is that the unobservable factors that might simultaneously affects the left and right hand sides of the previous regression do not vary across individuals when we include observed controls. It is also important to note that we are considering for this regression only observations from the Selector Stage. If we control for fixed effects in the regression we eliminate the most stable participant types that tend to play in line with the model's predictions. If we redo the previous analysis without considering the most stable individuals, the treatment' effect reduces their magnitude but they are still significant.[17]

Table 1.1 shows the regression results for different specifications of the baseline model. We report results using a logit model on the regression with standard errors clustered at the manager level, though the results are robust to many alternative specifications.[18] Consistently with the figure above, both the estimated coefficients of the $Treatment(p = 50)_i$ and $Treatment(p = 80)_i$ variables are negative and significant. Moreover, the estimated coefficient for $Treatment(p = 80)_i$ more than double the estimated coefficient of $Treatment(p = 50)_i$ in all specifications. Repeating these regressions with the 50% treatment omitted shows that there is significantly more decentralization in the 80% treatment than the 50% treatment. This confirms the monotonic relationship from Figure 1.6 that more accurate information leads to higher rates of centralization.

In Panel A of Table 1.1, the treatment variables capture the net effect of each level of information on the probability to decentralize, and the effect grows when we add demographic and risk preference controls as well as round dummies. In Panel B, we attempt to distill the net effect by separating the direct effect of information quality on the manager's decision from the indirect effect of what the manager has chosen in prior

[17] Standard errors of coefficient estimates are clustered by participants to allow for non-zero correlation of residuals amongst all observations belonging to the same participant. As a robustness check, we also cluster the standard errors of the coefficient estimates by round-treatment, to avoid correlations of the residuals at the session level not captured by the round fixed effects δ_r. Finally, we check the significance of our effects using a double clustering, by participant and round-treatment clusters. The main results do not change in any of these alternate specifications.

[18] We replicate these results using OLS and probit models. We also see the same results using random effects with bootstrapped standard errors. We do not report these results but we will provide them upon request.

rounds. The decision to decentralize is not affected by the profits from the previous round, but it is affected by the previous decisions made by the manager. Columns 5 and 7 shows that for every one unit change in the team heterogeneity, the log odds to decentralize increases. However, the original effects of the treatments on the probability to decentralized remained almost unchanged on column 5. This provides initial evidence of a weak relationship between the team heterogeneity and the level of information determining the treatment, which we return to in the next section. Column 6 shows that the organizational structure decision in the previous round has a positive and significant effect on current decentralization that reduces the magnitude of the direct treatment effect.[19] Finally, in the last two columns, we divide the sample between the first eight rounds played on the Selector stage (column 8) and the last eight (column 9). Column 8 shows that the direct effect is higher initially, compared to column 7, while the indirect effect is lessened. The opposite relationships appear in column 9. It suggests participants rely on their experience to learn through the experiment.

There are some secondary results on this regression that we do not report but that are worth mentioning. There is a positive and significant relationship between willingness to take on risk (using the Eckel-Grossman measure included in the controls) and the probability to decentralize. In other words, an agent that is more risk seeking is more likely to delegate decision rights to her workers.[20] We do not observe any significant effect of gender or the Cognitive Reflection Test (CRT). However, the U.S. sessions have a positive and significant impact on the probability to decentralize in all the specifications compared to those run in Spain.[21]

[19]Column 7 in Table 1.1 includes the lags of the team heterogeneity, decentralized decision and payoffs. While it may raise some concerns about multicollinearity, we observe that all the correlations (Pearson's Correlation Test and Spearman's Rank Test) between these variables are positive but modest (< 0.13) in the Selector stage for the participants with the role of managers. Moreover, the correlation between the decision to decentralize and the profits is not significant. In other words, there still is an important variation across observations on the Selector Stage to obtain unbiased estimated of coefficients.

[20]In our context, the less risky option from a manager's perspective is more related with her team composition. A strongly risk averse manager should choose a totally homogeneous team with both workers in the middle of the task space to equalize the ex ante expected task distance. In this case, the manager should be indifferent between the two types of organizational structures. However, it is also true that the optimal team composition in a decentralized organization is more heterogeneous than the optimal team composition in a centralized organization for all levels of information accuracy. Our result makes sense if the selection of a decentralized organization is correlated with the selection of a more heterogeneous team. This is the case as we will show later.

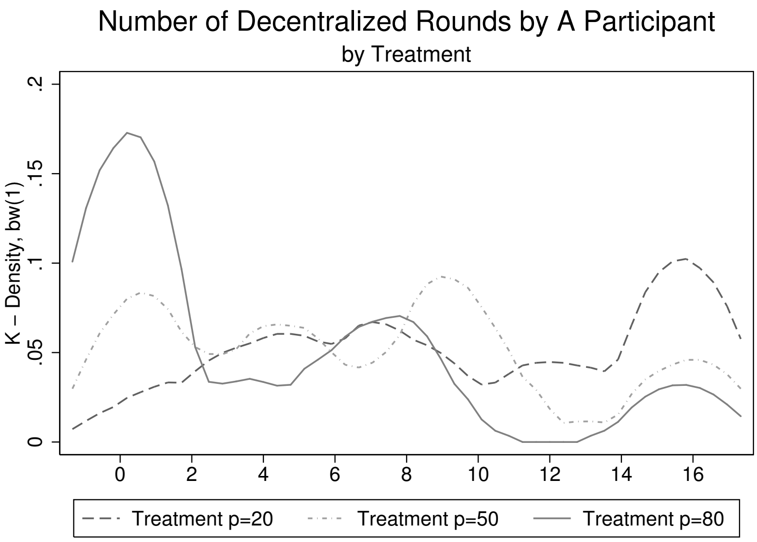
[21]We run again our basic econometric specification dividing our sample by country (Appendix A.3.).

	Panel A: Full Sample			Panel B: Including Lags				Rounds 1-8	Rounds 9-16
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Treatment(p=50)_i$	-0.701**	-0.958***	-0.962***	-0.924**	-0.947***	-0.556**	-0.592**	-0.791***	-0.416
	(0.35)	(0.36)	(0.36)	(0.36)	(0.35)	(0.26)	(0.25)	(0.26)	(0.29)
$Treatment(p=80)_i$	-1.513***	-1.822***	-1.829***	-1.842***	-1.897***	-1.238***	-1.319***	-1.474***	-1.193***
	(0.40)	(0.40)	(0.41)	(0.41)	(0.40)	(0.29)	(0.29)	(0.30)	(0.31)
$Payoff_{ir-1}$				0.009			0.005	0.010	0.001
				(0.01)			(0.01)	(0.01)	(0.01)
$Team.Heterogeneity_{ir-1}$					0.023***		0.020***	0.019***	0.020***
					(0.01)		(0.01)	(0.01)	(0.01)
$Decentralization_{ir-1}$						1.914***	1.867***	1.633***	2.080***
						(0.29)	(0.28)	(0.30)	(0.31)
$Constant$	0.414*	-1.602***	-1.663***	-1.846***	-2.619***	-2.079***	-3.031***	-3.132***	-2.813***
	(0.25)	(0.58)	(0.61)	(0.63)	(0.72)	(0.53)	(0.61)	(0.64)	(0.63)
$RoundDummies$	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Controls_i$	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. obs.	1424	1424	1424	1335	1335	1335	1335	623	712
N. clusters	89	89	89	89	89	89	89	89	89

Notes. * p< 0.1; ** p<0.05; *** p<0.01. Estimation of a logit model with standard errors clustered by subject. $Treatment(p=k)_i$ is a dummy variable taking value 1 if the manager knows each of the tasks with a probability k. $Decentralization_{ir}$ is a dummy variable taking value 1 if the subject i decentralized in round r, $Payoffs_{ir}$ are the payoffs per round in experimental currency obtained by subject i in round r and $Team.Heterogeneity_{ir}$ is the distance between positions selected by the subject i on round r. The controls by subject we are considering are the Eckel-Grossman risk aversion test, a cognitive reflection test, a dummy variable taking value 1 if Male, a dummy variable taking value 1 if the session was run in US and and a variable capturing different intervals of age.

Table 1.1: Organizational Structure Decision: Probability to Decentralize in Selector Stage

We next examine whether these initial results reflect a universal trend, or whether we can identify heterogeneity in subject types based on managers' decisions in the selector stage. For instance, if we observe an increase of sixteen decentralization choices, it could mean that half of the sample is decentralizing one more round or that one participant has decided to decentralize all her rounds. While the first example could be not taken as definitely proof of a change in behavior, the second is evidence of a change in the behavior of one subject. Figure 1.7 plots, for each treatment, a smoothed distribution of managers' decentralization choices in "x" rounds. Where "x" is the variable in the axis.



Notes. Kernel density approximation of the density of managers by number of rounds out of sixteen they chose to decentralize in the Selector stage.

Figure 1.7: Number of Decentralized Rounds by Managers

On the left hand side, we have the participants that decided to centralize in (nearly) every round. The highest concentration of participants in the 80% treatment is here. The number of participants on the left decreases as the level of information decreases. On the right hand side, where we find the participants that decided to decentralize in almost all the rounds, the order of the treatments is reversed. The highest concentration of the participants decentralizing in almost all rounds is in the 20% treatment and it decreases as the level of information increases. Notice as well that in the 50% treatment we have different modes and the participants are divided more equally among all of them.

We use the modes in Figure 1.7 to classify the participants in 3 different categories in terms of their stability in the selection of an organizational structure (SOS). We classify a manager as a centralizer (C) if she decides to centralize in at least 12 rounds of the "Selector" Stage. She is a neutral player (N) if she decided to centralize between 5 and 11 rounds and any manager centralizing between 0 and 4 rounds is classified as a decentralizer (D). Table 1.2 shows us the distribution of types by treatment. We chose this classification for simplicity. In Appendix A.4 we consider an alternate classification with five types as a robustness check.

Classification/Treatment	p=20	p=50	p=80	Total
D	13	5	3	21
N	10	13	9	32
C	7	11	18	36

Notes. The figure plots the number of participants given their classification on the stability on organizational structure.

Table 1.2: Participants distribution by Stability on Organizational Structure

Notice that there is a concentration on participants in the diagonal of the table. There are more decentralizers in the 20% treatment, more neutral players in the 50% treatments and more centralizers in the 80% treatment. This relationship between treatment and stability of organizational structure (SOS) decision is highly significant (Fisher's exact test, p = 0.011). As a consequence, we confirm that the treatment is important to determine the proportion of participants in each of the SOS categories.

Our main result in this section states that the managers did not decentralize as much as predicted by the model. However, they clearly decentralize more with lower levels of information, and this decentralization can be explained by a shifting mass of participants from being centralizers to decentralizers following our classification by SOS. At the best of our knowledge, this is the first empirical evidence of this already well-known theoretical prediction. Other minor results are that the degree of risk aversion affects the probability to decentralize. More risk averse agents would try to keep more control and would choose a more centralized organization. The country of origin matters in this decision as well. Spanish participants are more reluctant to decentralize than US participants, specially in the 50% treatment (in general, country effects were minor – Appendix A.3).

1.5.2 Team Composition

To analyze the team composition selected by managers, we study separately their behavior in the first two stages and in the Selector stage. Their decisions in the first two stages allow us to understand their team selections when they can not choose an organizational structure. In those cases, the managers know only the accuracy of the level of information and they must adapt their team selection to the type of organizational structure they faced. In the selector stage they have the same information as before plus the experience from the previous stages working in each organizational structure.

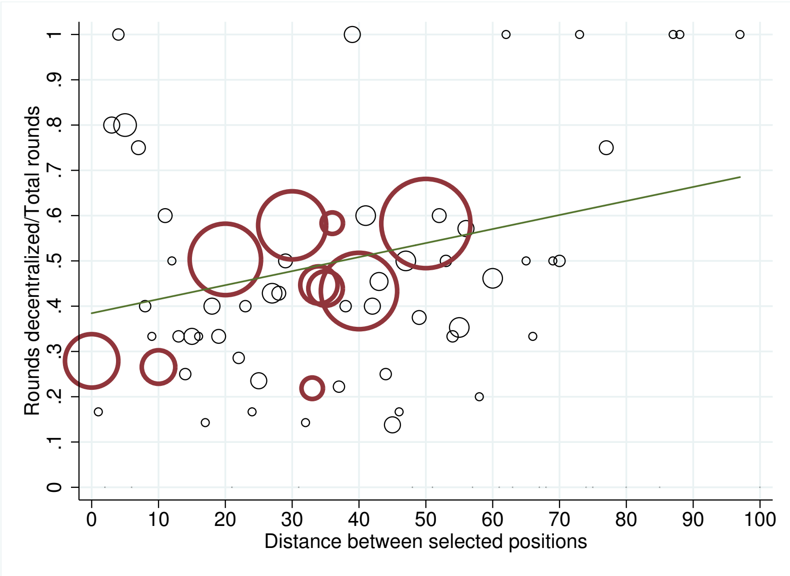
A brief overview shows that the average distance between positions in the centralized and decentralized stages is 29.83 and 29.40, respectively. On aggregate, then, we see no clear difference. In the selector stage, the average distance between positions in the centralized rounds is unchanged at 29.53, but this grows significantly to 33.16 in the decentralized rounds (Two-tail t test, $p = 0.0001$; Mann-Whitney two-tail test, $p = 0.0003$). This direction is in line with prediction 2 beyond the fact that the average distance in the decentralized rounds of the selector stage is not as high as predicted by the model. It also provides initial evidence that subjects may be learning to play more optimally with experience, at least in the decentralized rounds.[22] A pairwise test is suggestive but not conclusive given the repeated decisions made by each manager. In the rest of the section we show a more robust test on the relation between team composition, the decision to decentralize and the treatments.

Team heterogeneity and decentralization

Figure 1.8 plots the percentage of decentralized rounds on the distance between positions in the Selector Stage. We use the frequency of the distance between positions to weight each observation. It determines the size of the bubble on the scatter plot. Sev-

[22]We took average distance among positions selected as a measure of the team heterogeneity. It is also informative about the positions selected since most of the time those positions are symmetric around the 50 as we will see in this section.

enty two percent of the sample is captured by the clusters shown in red.[23] These clusters also contain 77% of the total number of decentralized rounds during the Selector Stage. The correlation shown by the linear trend-line is approximately 0.1 and it is significant at the 5% level.[24]



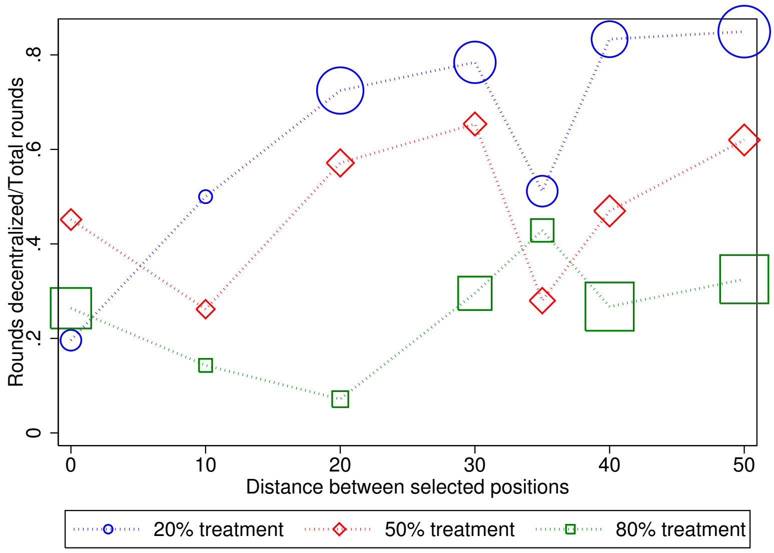
Notes. Plot the percentage of decentralized rounds in the Selector Stage (y-axis) by distance between positions (x-axis) managers selected. The observations are weighted by the frequency of each value of the distance between positions. The bold red bubbles represent the 72% of all the rounds played on the Selector Stage. The green line is an linear approximation of the correlation.

Figure 1.8: Decentralization and distance between positions

In Figure 1.9 we focus on the subsample emphasized by the red bubbles in Figure 1.8 and separate them by treatment. There is a positive relation between decentralization and team heterogeneity in all treatments. The probability to decentralize per distance between positions increases as the level of information decreases in most of the cases. The main exception are when teams are perfectly homogeneous, where the organizational structure does not affect the final payoff.

[23]They represent 10 different values of the distance between selected positions: 0, 10, 20, 30 , 33, 34, 35 and 36, 40 and 50.

[24]We obtained a similar result using a Spearman rank correlation test.



Notes. Plot the percentage of decentralized rounds in the Selector Stage (y-axis) by distance between positions (x-axis). The observations are weighted by the frequency of each value of the distance between positions. The data represents the 72% of all the rounds played in the Selector Stage. We collapsed the observations belonging to the interval form 33 to 36 assigned to the distance 35 for clarity.

Figure 1.9: Decentralization and distance between positions: By treatment)

The previous figures suggest a positive and significant correlation between team heterogeneity and the tendency to decentralize. We confirm this relationship using OLS regressions in Table 1.3, again clustering standard error by manager. Panel A shows that there is a strong effect of decentralization on team heterogeneity. Interestingly, the treatments have no direct effect on team heterogeneity once we control for the organizational structure. In Panel B we see that all lagged variables have a positive and significant effect on team heterogeneity even when we consider them together. Notice that the lagged heterogeneity in column 5 removes the significant effect of decentralization in the current round, while the lagged decentralization decision in column 6 is significant but does not reduce the significance of the current decentralization decision. This suggests that the prior team heterogeneity impacts current heterogeneity more than current decentralization, while decentralization itself has an additive effect over time.

	Panel A: Full Sample			Panel B: Including Lags				Rounds 1-8	Rounds 9-16
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Decentralization_{ir}$	4.384*	4.947**	4.987**	5.331**	1.432	4.141**	0.456	0.415	0.279
	(2.33)	(2.43)	(2.45)	(2.40)	(1.06)	(1.81)	(1.05)	(1.60)	(1.39)
$Treatment(p = 50)_i$		1.427	1.436	1.377	0.629	2.024	0.905	0.728	1.204
		(3.31)	(3.32)	(3.25)	(1.29)	(3.31)	(1.28)	(1.62)	(1.41)
$Treatment(p = 80)_i$		2.045	2.061	2.213	1.072	3.392	1.417	1.348	1.472
		(3.66)	(3.68)	(3.64)	(1.48)	(3.74)	(1.48)	(1.79)	(1.64)
$Payoff_{ir-1}$				0.144***			0.079***	0.137***	0.029
				(0.05)			(0.03)	(0.04)	(0.05)
$Team.Heterogeneity_{ir-1}$					0.618***		0.612***	0.568***	0.653***
					(0.06)		(0.06)	(0.07)	(0.06)
$Decentralization_{ir-1}$						3.437**	2.203**	1.109	3.281**
						(1.71)	(0.99)	(1.45)	(1.48)
Constant	37.292***	36.602***	37.955***	33.193***	13.129***	36.136***	11.419***	11.854**	9.616**
	(6.04)	(6.36)	(6.37)	(6.74)	(4.10)	(6.53)	(4.09)	(4.65)	(3.69)
$RoundDummies$	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Controls_i$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. obs.	1424	1424	1424	1335	1335	1335	1335	623	712
N. clusters	89	89	89	89	89	89	89	89	89

Notes. * p< 0.1; ** p<0.05; *** p<0.01. OLS estimation with standard errors clustered by subject. $Treatment(p = k)_i$ is a dummy variable taking value 1 if the manager knows each of the tasks with a probability k. $Decentralization_{ir}$ is a dummy variable taking value 1 if the subject i decentralized in round r, $Payoffs_{ir}$ are the payoffs per round in experimental currency obtained by subject i in round r and $Team.Heterogeneity_{ir}$ is the distance between positions selected by the subject i on round r. The controls by subject we are considering are the Eckel-Grossman risk aversion test, a cognitive reflection test, a dummy variable taking value 1 if Male, a dummy variable taking value 1 if the session was run in US and and a variable capturing different intervals of age.

Table 1.3: Team Composition: Distance between selected positions in Selector Stage

From Table 1.1, we know that there is a correlation between the decision to decentralize in round r and the the lagged decisions to decentralize and team heterogeneity. As a consequence, the observed effect is not unexpected. Comparing regressions in Table 1.1 and 1.3 highlights different drivers of these two decisions. Beyond the fact that both decisions depend on the lagged decision of the individuals, the decision to decentralize depends on the treatments but not on lagged payoffs while for team heterogeneity the opposite is true. Finally, the last two columns split the selector stage in two. As in Table 1, we see evidence of learning. Column 8 suggest that agents are relying more on payoffs and their previous team heterogeneity decision since they may not have settled on the optimal organizational structure. Once they have determined their preferred organizational structure, they do not rely anymore on prior payoffs but on their decentralization decision.

	All Sample			1-8 rounds	9-16 rounds
	(1)	(2)	(3)	(4)	(5)
$N.Dec.rounds_i$	0.517*	0.661**	0.859**	0.728**	0.990***
	(0.27)	(0.30)	(0.35)	(0.36)	(0.37)
$Treatment(p = 50)_i$			3.281	3.389	3.174
			(3.47)	(3.51)	(3.67)
$Treatment(p = 80)_i$			5.428	5.038	5.817
			(4.14)	(4.03)	(4.45)
$Constant$	27.549***	36.957***	35.123***	35.708***	34.537***
	(2.54)	(6.10)	(6.51)	(6.49)	(6.71)
$Controls_i$	Yes	Yes	Yes	Yes	Yes
N	89	89	89	89	89

Notes. * p-value< 0.1; ** p-value<0.05; *** p-value<0.01. The table provides an estimation of the total number of rounds decentralized by each participant with a managerial role against the average distance between positions selected by that participant. We pursue an OLS estimation with robust standard errors. In this regression we have only one observation by participant.

Table 1.4: Team Heterogeneity in the Selector Stage: Average distance between positions selected

The dynamic nature of the experimental setting creates the dependence of workers' decisions on their history of play. It generates a more cumbersome interpretation of estimated coefficients. Another way to analyze the relation between team heterogeneity and decentralization is to regress the average distance between positions in the Selector stage on the total number of decentralized rounds ($N.Dec.rounds$ on Table 1.4). In this regression, we have one observation per individual. The correlation between these two variables is positive and significant, but we can not establish a causal relationship between them. In column 3, the impact to decentralize one round more increases the distance between positions by 0.86, but when we separate the first 8 form the last 8 rounds we realize that the effect is getting stronger on the second part of the stage up to 0.99. This evidence suggest that the experience of the agents reinforce the positive relation between team heterogeneity and decentralization. As before, the treatment has no impact on team heterogeneity. All the evidence presented on this subsection support prediction 2 on the previous section.

Centralized rounds

We now look more closely at subject behavior in the centralized rounds to address prediction 3. Table 1.5 presents the average position selected by the participants in the centralized rounds of the centralized and selector stages, respectively. In the last two columns we have our predicted optimal positions in a centralized organization. The average positions are not sensitive to treatment as the model predicts. However, the variance of the positions decreases in the 50% and 80% treatment when we compare the selector stage with the centralized stage, suggesting again that subjects are becoming more stable in their placement.

The model predicts that centralized teams should become more heterogeneous as the information improves, with the optimal distance between positions growing from 16 to 30 and up to 42 in the 80% treatment. We do see significantly more heterogeneity when comparing the 20% and 50% treatments (27.99 up to 32.56; two-tail t test $p = 0.0042$, MW $p = 0.031$ - again, a pairwise test here is illustrative but not necessarily conclusive). Interestingly this disappears when we move to the 80% treatment, as the distance falls to 29.04. Likewise, in the centralized rounds of the selector stage we see the distance between positions grow from 26.19 to 31.68 moving from the 20% to 50% treatments, but again fall to 29.71 in the 80% treatment. We will revisit this curious "pinch" effect.

The predictions of the model are not satisfied on aggregate. However, a closer look

		C. Stage		S. Stage		Opt. Pos.	
Treat.	Stats.	Pos 1	Pos2	Pos1	Pos 2	Pos1	Pos 2
20%	Mean	35.40	63.39	35.53	61.72	42	58
	SD	14.34	13.84	17.56	15.37		
	N	300	300	191	191		
50%	Mean	32.93	65.49	33.15	64.83	35	65
	SD	12.57	13.15	11.14	11.15		
	N	290	290	265	265		
80%	Mean	35.04	64.11	35.32	65.03	29	71
	SD	12.45	12.99	10.94	10.61		
	N	300	300	360	360		

Notes This table reports the mean, standard deviation and sample size of the positions selected by managers in the centralized stage and in the centralized rounds of the selector stage. The last two columns indicate the optimal worker positions for a centralized organization by treatment.

Table 1.5: Average positions in centralized rounds

at team selection by treatment provides some deeper insight. In Figure 1.10, we plot team selection in centralized rounds by treatment and by stage (Centralized stage, panel A and; Selector stage, panel B). The x-axis denotes the right-most worker on the 0-100 scale and the y-axis denotes the left-most worker. The downward sloping line denotes all symmetric teams.[25] The optimal positions are indicated by the crossing dotted lines. We see a concentration of perfectly homogeneous teams in both stages. In other words, the participants decided to assign the same position to their team members, and in 95.6% of those cases the managers placed both workers at 50. It is particularly surprising on the 80% treatment where the agent has more information about the tasks. We return to this later.

Aside from these observations, the next modal teams are very close to the optimal team predicted by the model - 16, 30, and 42 respectively as information accuracy improves. Moreover, the concentration of observations on these optimal points increases in the centralized rounds of the selector stage in the 80% treatment. In the 20% treatment, managers shift to more homogeneous teams in the selector stage, though there are no-

[25]For visual clarity, we omit bubbles for single observations, though these are included in the un-edited graphs in Appendix A.5.

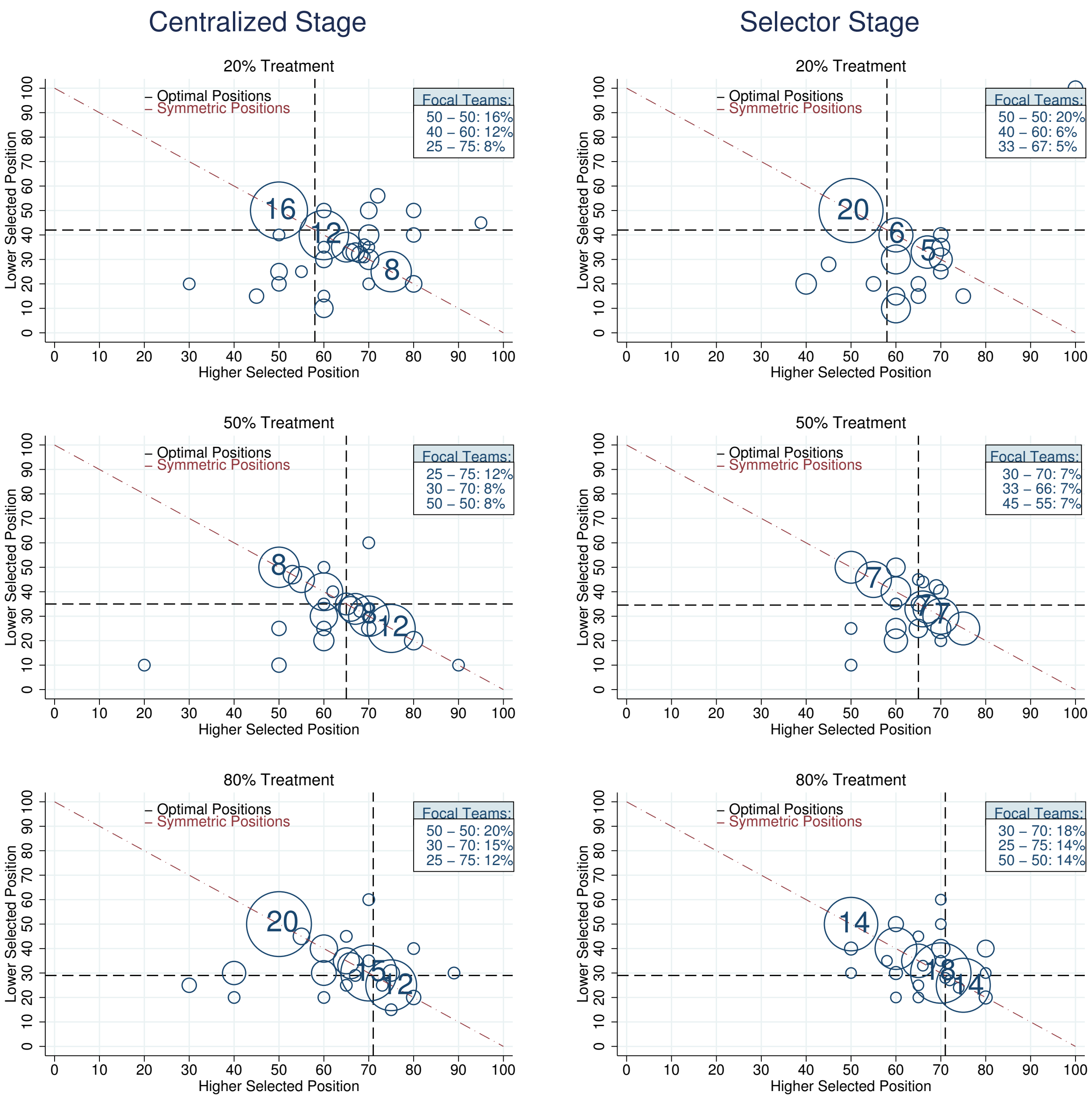
tably fewer managers choosing centralization in this treatment. Another promising sign that managers are improving their composition decisions is that as we move from the centralized stage to the selector stage, we see fewer observations far from the symmetry line for the 50% and 80% treatments. Using a Two-sample Kolmogorov-Smirnov test we find that the distributions in the centralized stage and selector stage are statistically different only in the 20% treatment (p=0.003).

Lastly, we compare the distance between positions across treatments by manager type using the manager classification from section 1.5.1, omitting observations with perfectly homogeneous teams.[26] When we separate centralizers from all other manager types we find no significant difference in team heterogeneity. Looking instead at managers centralizing in at least fourteen rounds of the selector stage, we see that they choose teams significantly closer to the model's prediction than other managers, but this significance is not robust to a more inclusive classification of centralizers.

Decentralized rounds

We next turn our attention to decentralized rounds in order to address prediction 4. Table 1.6 presents the average position selected by managers in the decentralized stage and decentralized rounds from the selector stage, along with the optimal positions for a decentralized organization.

[26]With perfectly homogeneous teams, managers are indifferent between a centralized and decentralized structure. Our aim here is to consider those teams for whom team composition matters under a centralized structure.



(a) Panel A

(b) Panel B

Notes. Plot the team composition selected on the centralized rounds played by stage and treatment. The x-axis represents the right-most worker, while the y-axis represents the left-most worker per team. The size of the bubble are determined by the weight that team composition have on each treatment-stage subgroup. The dotted black lines are the optimal positions predicted by the model on centralized organizations given the level of information. The inverse red dash-dot diagonal represents the team compositions that are symmetric around the expected ex-ante task.

Figure 1.10: Team Composition on the Centralized Rounds

Treat.	Stats.	D. Stage Pos 1	D. Stage Pos2	S. Stage Pos1	S. Stage Pos 2	Opt. Pos. Pos1	Opt. Pos. Pos 2
20%	Mean	33.80	66.23	33.47	68.04	27	73
	SD	14.56	14.56	14.52	12.73		
	N	300	300	289	289		
50%	Mean	33.28	62.46	32.94	64.20	27	73
	SD	14.66	17.15	10.16	11.59		
	N	290	290	199	199		
80%	Mean	36.63	63.22	33.06	65.98	27	73
	SD	13.38	14.04	11.33	12.18		
	N	300	300	120	120		

Notes. This table reports the mean, standard deviation and sample size of the positions selected by managers in the decentralized stage and in the decentralized rounds of the selector stage. The last two columns indicate the optimal worker positions for a decentralized organization by treatment.

Table 1.6: Average positions in decentralized rounds

As in the centralized structure, the average positions selected by the participants are not the same as those predicted by the model. In the decentralized stage, we again observe the "pinch" effect, in which the average team composition becomes more homogeneous as the level of information increases (32.43 to 29.18 to 26.59 for the 20%, 50%, and 80% treatments, respectively). Teams in the 20% treatment are significantly more heterogeneous than in the 80% treatment (two-tail t test, $p = 0.0006$, MW, $p = 0.0016$).[27] In the decentralized rounds of the Selector stage, we see no such relationship. In the Selector stage, the level of information does not affect the optimal positions, in line with the theoretical predictions. However, notice that the positions selected are more homogeneous than those predicted by the model. If we compare the decentralized stage with the selector stage, there is an improvement in team selection in all treatments but it is significant only in the 80% treatment (two-tail t test $p = 0.0058$; MW $p = 0.0085$).

In Figure 1.11, we replicate Figure 1.10 for decentralized rounds by treatment and

[27] The difference between the 20% and 50% treatment is also significant with MW test ($p = 0.0305$), but the difference between 50% and 80% treatment is not.

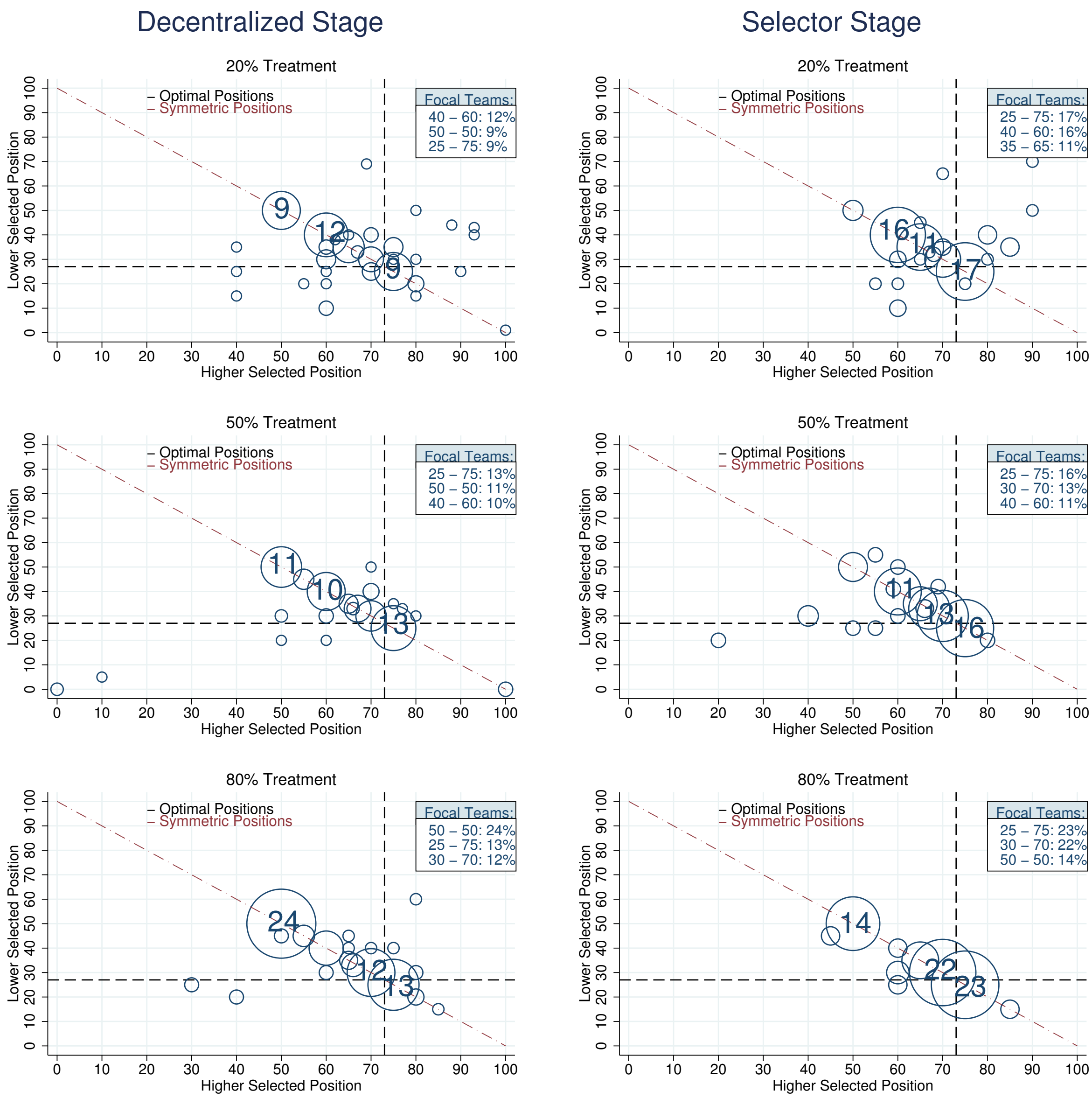
by stage.[28] There is again a high concentration of perfectly homogeneous teams in all treatments, even higher than in the centralized stage for the 50% and 80% treatments. However, in the decentralized rounds of the selector stage we observe a movement towards more heterogeneous teams in all treatments. As with the centralized rounds, we see better convergence in the selector stage towards the model's predicted distance between positions, which is 46 for all treatments under decentralization. A Two-sample Kolmogorov-Smirnov test shows that the distributions on the decentralized stage and selector stage are marginally statistically different between the 20% and 80% treatments ($p = 0.056$ and $p = 0.057$ respectively).

As in the previous section, we examined the relationship between manager types and team heterogeneity in decentralized rounds. We separate decentralizers (those who chose a centralized structure in the selector stage fewer than five times) from all other managers and here we see some significant differences in team composition. Decentralizers choose more heterogeneous teams than other subjects, and the gap is significant in the 50% and 80% treatments for the decentralized stage (two-tail t test, $p = 0.0135$ and $p = 0.0577$ and MW test, $p = 0.0015$ and $p = 0.0564$, respectively). When we look at the decentralized rounds of the selector stage, the gap persists but is only significant in the 50% treatment (two-tail t test and MW, $p = 0.0000$). There are significant differences in the team composition selected by decentralizers and non-decentralizers in the decentralized rounds.

Unexpected team homogeneity: Examining "50-50" teams

We return now to the curious effect wherein managers reduce team heterogeneity as their information improves. Moreover, we still have not given any explanation for the amount of participants choosing completely homogeneous teams, particularly in the 80% treatment (see Appendix A.6 for a full categorization of case). These instances are remarkably common in both organizational structures and are most frequent in the 80% treatment. We find six subjects who extensively select the 50-50 team composition (Two subjects do this only in the centralized stage, two in the decentralized stage, and two more in both stages). It is surprising to see this behavior predominantly in the treatment

[28] Again, we point out that bubbles for single observations have been omitted to improve readability. We include the un-edited bubble graphs in Appendix A.5.



(a) Panel A (b) Panel B

Notes. Plot the team composition selected on the decentralized rounds played by stage and treatment. The x-axis represents the right-most worker, while the y-axis represents the left-most worker per team. The size of the bubble are determined by the weight that team composition have on each treatment-stage subgroup. The dotted black lines are the optimal positions predicted by the model on decentralized organizations given the level of information. The inverse red dash-dot diagonal represents the team compositions that are symmetric around the expected ex-ante task.

Figure 1.11: Team Composition on the Decentralized Rounds

where the agents have the best chance of observing the realized tasks. Risk could be a potential issue, but the predictions of the model do not vary by risk preference.[29]

The repeated nature of the experiment allows us to identify a possible cause of this behavior. Participants seem to react strongly to bad outcomes in a round by changing their team composition in the subsequent round. The occurrence of 50-50 teams is predominantly seen in these situations, though the direction of the manager's reaction depends on the positions they selected previously. To explore this conditional effect we use the following specification:

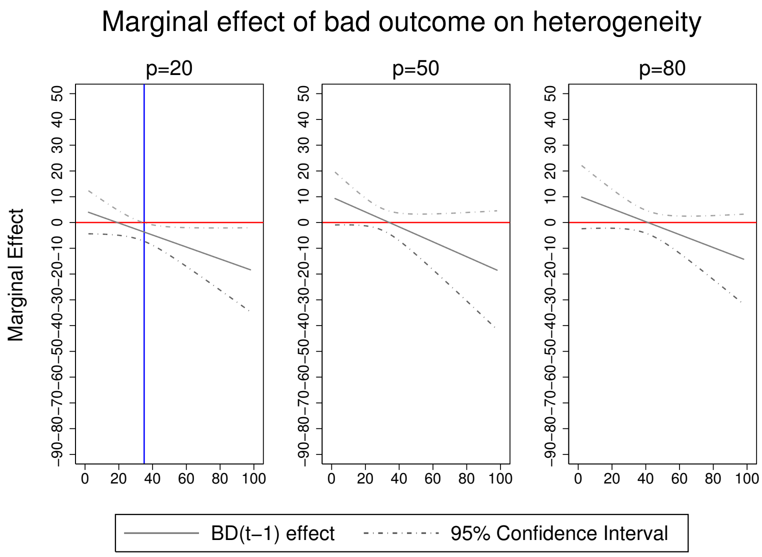
$$dist\_pos_{(i,t)} = \alpha + \beta dist\_pos_{(i,t-1)} + \delta BAD_{(i,t-1)} + \gamma dist\_pos_{(i,t-1)} BAD_{(i,t-1)} + \mu_{(i,t)} \quad (1.1)$$

Where $dist\_pos_{(i,t)}$ is the distance between positions selected by participant i in round t, $BAD_{(i,t)}$ is a dummy variable for bad outcomes taking a value of one if the payoff of the participant i in period t, π_{it}, is less than or equal to 25 and $\mu_{(i,t)}$ is an error term. We consider this specification of bad outcomes as our loss measure because 25 is the average payoff that a participant would receive if she plays the least risky strategy of selecting a homogeneous team at 50-50.

The regression output is omitted to save space, but we plot the marginal effects of bad outcomes by distance between positions for each treatment when the distance between positions is not equal to zero in round $t - 1$. We focus our attention here on the centralized and decentralized stages. In these stages, the participants may only change their selected positions in response to an unexpected or undesirable outcome in the previous round. The Selector stage is problematic because managers could change both team composition and organizational structure, which makes identification less clear. Figure 1.12 shows the marginal effects of bad outcomes in the centralized stage with 95% confidence intervals. The blue vertical line indicates ranges over which the effect is significantly different than zero. In all treatments we see a pattern in which managers with more heterogeneous teams respond to bad outcomes by selecting more homogeneous teams. This is significant for the 20% treatment for distances above 35 and marginally significant (at the 10% level) in all treatments when the distance between positions is above 40. In the 20% treatment, this amounts to two fifths of decisions made

[29] Analyzing the characteristics of the participants following a fix 50-50 strategy, we see mostly men with extreme risk preference measures - either strongly risk averse (1 in the EG test) or strongly risk seeking (5 in the EG test).

when the team composition is not perfectly homogeneous, and one third of all decisions. Also note that managers with very homogeneous teams respond to bad outcomes by increasing the distance between positions. Recall that the optimal distance between positions in a centralized structure for the 20% treatment is 16. Therefore, the reaction could simply be managers learning to play the optimal strategy. We cannot rule that out, but the consistency of the result for all information levels suggests a broader reaction that can't be explained by the model.



Notes. Plot of marginal effects (y-axis) by distance between positions (x-axis) for each treatment in the centralized stage with 95% confidence bounds. The vertical blue line separates the areas in the graph where we have significance effects from the areas where we do not.

Figure 1.12: Reduced heterogeneity: Centralized stage ($\pi_A \leq 25$)

Note that this phenomenon may be triggered by low payoffs even when managers play the optimal strategies as a consequence of the random realization of the tasks in the game. Although the likelihood to have a low payoffs when managers choose the optimal positions is lower, it can be enough to drive team selection away from the optimal strategy.

Figure 1.13 replicates this analysis for the decentralized stage of each treatment. We see the same negative trend in marginal effects in the 20% and 80% treatments. While the general trends are similar to what we see under centralization, we see clear changes in the x-intercept, particularly for the 80% treatment. The managers reduction in team heterogeneity in response to bad outcomes now begins as low as 25 (compared to just over 40 in the centralized stage), which accounts for nearly half of all observations (more than 60% of observations if we ignore instances with perfectly homogeneous teams). In the 20% treatment, both the positive marginal effect for distances below 20 and negative effect for distances above 50 are perfectly in line with the theoretical prediction (the optimal distance is 46 regardless of treatment under decentralization). However, manager behavior in the 80% treatment is counter to the model, as they reduce team heterogeneity after a bad outcome if their previous team distance was greater than 25.

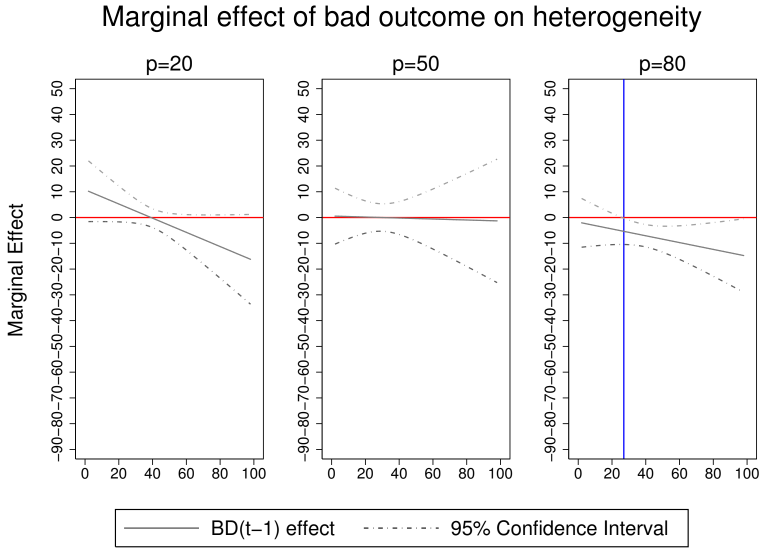
What exactly is causing managers to react this way, reducing heterogeneity in response to bad outcomes? One explanation is that we are observing something akin to loss aversion (Kahneman and Tversky, 1979; Koszegi and Rabin, 2006). However, the exhibited behavior is also potentially consistent with Selten's learning direction theory (Selten and Stoecker, 1986; Selten and Buchta, 1999), in which an errant behavior is corrected for by moving farther in the opposite direction to the prior wrong action. While learning direction theory cannot explain the fact that we see the strongest reactions in the direction of more homogeneity when this is further in the ”wrong” direction from optimum, we cannot conclusively rule out either explanation.

In Appendix A.7 we consider an alternative measure for bad outcomes in the decentralized stage, where the workers' task reallocation decision was suboptimal from the manager's standpoint.[30] The results using this alternative measure show that the loss aversion result is very robust and not driven by our choice to use payoffs less than or equal to 25. We again see significant and negative marginal effects in the 20% and 80% treatments very close to those reported above.[31]

We may consider another potential explanation for the behavior in the decentralized rounds of the 80% treatment. In the decentralized stage, team composition is the only decision made by managers. As such, managers who want to react to a bad outcome may do so by changing their team composition. Increasing the distance makes

[30] We did not choose this as our primary measure because although these realized conflict of interest are intuitively appealing, there are many rounds (particularly in the 20% and 50% treatments) where the managers do not observe both tasks ex-post, and so cannot verify that a conflict of interest has taken place. In fact, the results are even stronger for the 20% treatment even accounting for the lower number of observations.

[31] For instance, the marginal effect is significant and negative in the 80% treatment for all distances above 28, as compared to 25 using the payoff threshold measure.



Notes. Plot of marginal effects (y-axis) by distance between positions (x-axis) for each treatment in the decentralized stage with 95% confidence bounds. The vertical blue line separates the areas in the graph where we have significance effects from the areas where we do not.

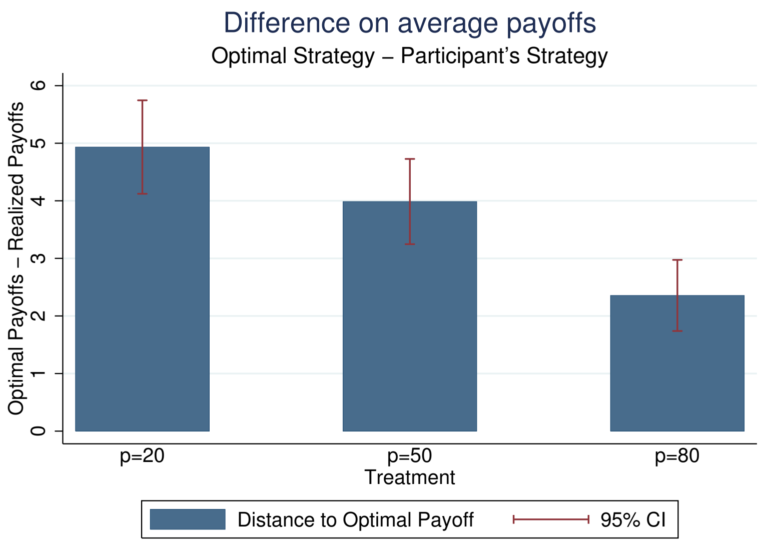
Figure 1.13: Reduced Heterogeneity: Decentralized Stage ($\pi_A < 25$)

it more likely that further bad outcomes will be seen, even though it also increases expected payoffs. Therefore, by narrowing the distance between positions the managers seem willing to forego expected earnings in order to avoid observing bad outcomes by controlling the one factor they can, in line with the literature on the control premium literature discussed earlier. This is more common in the 80% treatment because, with better information, managers more frequently observe the task positions and can therefore verify bad outcomes more often, particularly outcomes that result in a conflict of interest, as discussed in the appendix.

The reaction to bad outcomes plays an important role in team composition. It helps explain the high concentrations of zeroes in the early stages of the experiment and the lack of heterogeneity in the final average positions. If we only consider cases of immediate reactions to a bad outcome (that is, one period later), we find that the effect can explain 30% of all observations of perfectly homogeneous teams. But, if we consider all rounds after a bad outcome in which the managers consecutively position their team at 50-50, the reaction effect can explain up to 50% of the cases.

1.5.3 Participants' payoffs

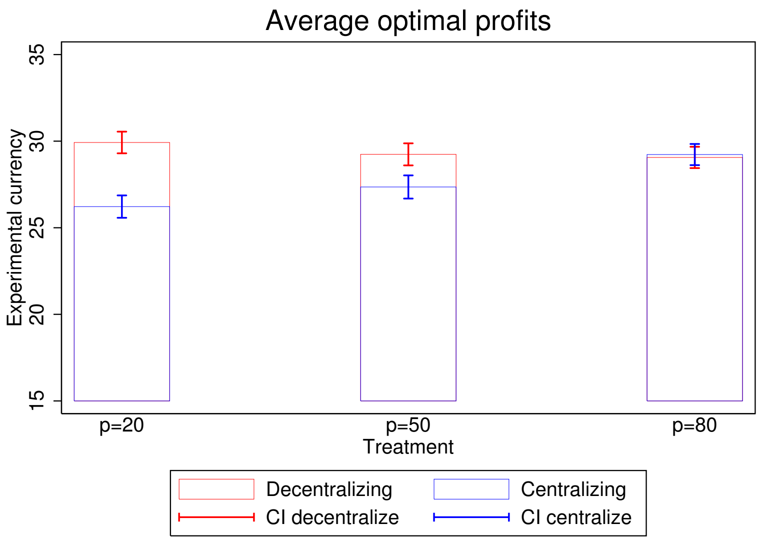
The interrelatedness of the organizational structure and team composition decisions make it difficult to disentangle the effect of each on subject payoffs. Comparing average earnings does not reveal much, as we see mean payoffs by information condition of 24.99, 25.25, and 26.70 for the 20%, 50% and 80% conditions, respectfully. Not surprisingly, average payoffs increase as information improves. However, we can see something informative by looking at how much subjects could have earned from decisions in line with theoretical predictions (i.e. how much money they are "leaving on the table"). With known ex-ante optimal decisions and ex-post realizations, we calculate the payoff each manager would have earned in each round had she played the optimal decentralized strategy, and subtract the manager's realized earnings in the round. Figure 1.14 shows this average difference in payoffs per round for managers in each treatment. While all treatments are under-performing their optimal strategy, the better information in the 80% condition shields managers from under-performance relative to the 20% and 50% conditions.



Notes. This graph plots the difference between the counter-factual payoffs that would have been obtained using the optimal strategy minus the actual payoffs realized by managers, separated by information condition.

Figure 1.14: Underperformance of managers relative to optimal strategy

While Figure 1.14 illustrates that managers are falling short of optimal payoffs on average in each treatment, it cannot identify the reason for under-performance. Specifically, are managers earning less due to an error in organizational structure or an error in team composition? In Figure 1.15 we use the observed outcomes in each round of the selector stage to compare the hypothetical earnings from playing the optimal decentralized strategy vs a centralized strategy that used optimal team composition. We see a clear advantage in realized payoffs from the decentralized strategy in the 20% and 50% condition, but it disappears in the 80% condition. Therefore, some of the under-performance seen in Figure 1.14 must be due to team composition.

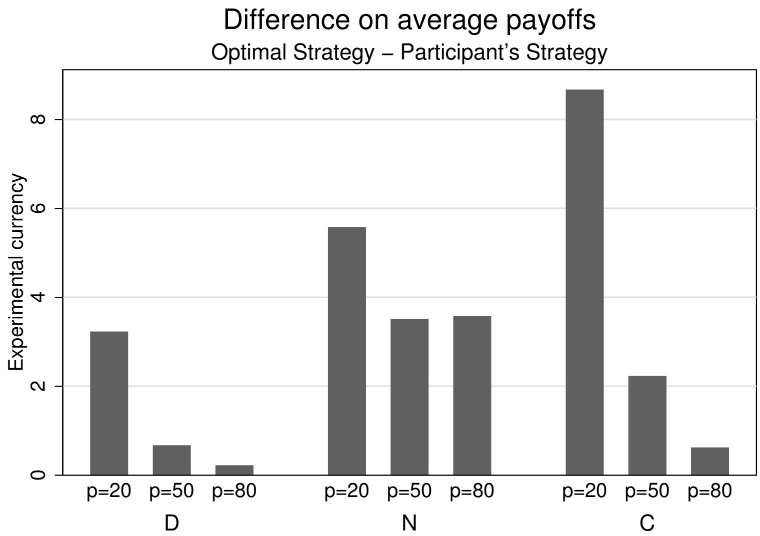


Notes. This graph plots the average payoffs per round the managers could have obtained by followed the optimal decentralized strategy (the red lines) or the optimal centralized strategy (the blue lines).

Figure 1.15: Payoffs under the optimal decentralized and centralized strategies

Using the optimal decentralized strategies the average payoffs per round per participant would be around 29 in all the treatments. Second, using the optimal centralized strategies (a "second-best" benchmark) we can observe that average payoffs are increasing with the accuracy of information. Critically, the optimal decentralized strategy outperforms the optimal centralized strategy in the 20% and 50% treatment but there is no significant difference in the 80% treatment between both strategies. Finally. we notice that the differences in performance between this strategies is monotonically decreasing as the level of information increases. All the results are in line with the model predictions.

Figure 1.16 replicates the results from Figure 1.14, broken down by manager type.[32] All managers saw the worst performance in the 20% treatment, but performance generally improves as the information accuracy rises. Additionally, decentralizers come closest to their optimal benchmark in all treatments. Recall that the 20% treatment has the highest amount of decentralizers while the 80% has the lowest amount, as shown in Table 1.2. This highlights the interaction between information quality and organizational structure. The learning process may be affected by the quality of information. Since managers saw fewer realized tasks in the 20% treatment, they had less information by which to adjust their strategy. Alternatively, there is a higher cost for the participants who do not decentralize as the level of uncertainty increases, and so the feedback is less powerful in changing organizational structure in the 80% treatment.



Notes. Plots of the average difference per round of the manager payoffs obtained from playing the optimal decentralized strategy and the real payoffs obtained by the participants during the experiment in the selector stage, separated by manager type.

Figure 1.16: Difference on average payoffs: Optimal strategy - participant's strategy

These results make perfect sense when we consider the literature on the control

[32]In Figure 1.16, we do not include the participants using the same position for both workers. As we explained before, those participants are indifferent between the two types of organizational structures.

premium. It is costly for the participants to maintain control in all the decisions affecting their final payoffs (in our case, selecting a centralized organizational structure). Furthermore, centralization is more costly for neutral managers in situations where the information is rich but it is more costly for centralizers when the information is poor.

We can derive an incomplete estimate of the control premium in our environment by taking the difference between the optimal payoffs and the realized payoffs of decentralizers as the cost of a less heterogeneous team. This difference, compared with the difference obtained by centralizers, could be interpreted as a control premium. Following this protocol, we see a control premium that ranges from 1% of the potential payoffs in the 80% treatment to 18% of the potential payoffs on the 20% treatment. Also, the cost of a less heterogeneous team is around 40 - 60% of this control premium estimate. Again, this evidence is merely suggestive and further analysis is needed, though it does match the range of control premium estimates observed in prior studies.

1.6 Simulation Results

The main aim of the previous experiment was to identify how managers jointly choose an organizational structure and team composition under different levels of information. We focused on two organizational structures and a uniform distribution of tasks in order to reduce subject confusion. The results are informative, but raise two particular questions that we investigate here. The first issue stems from the lack of change in team heterogeneity as information quality improves in centralized teams. Given these ”fixed” positions, are managers doing well in the organizational structure task? Specifically, how would payoff maximizing managers allocate decision rights in this environment with fixed team heterogeneity? Additionally, are the results or predictions reliant on a uniform distribution of tasks? We provide evidence that the model is robust to any symmetric unimodal distribution of tasks and simulate the behavior under several such distributions. While these questions merit further empirical study, we use Monte-Carlo simulations to gain some initial insight.

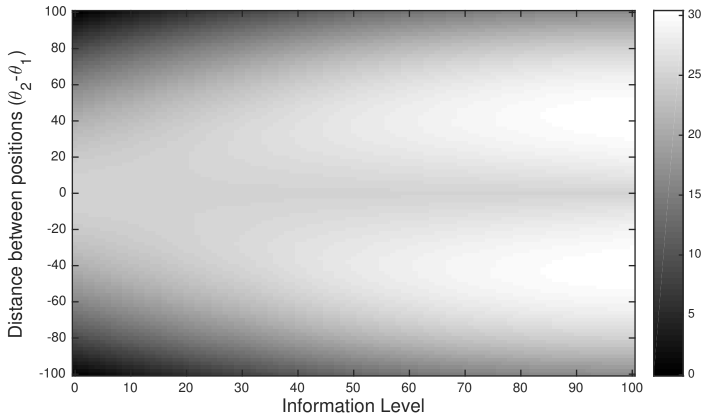
Our simulations generate behavior from 100 managers over 500 rounds each where the tasks are randomly drawn from a uniform distribution. We apply the different switching tasks rules active in each of the different organizational structures on a grid determined by the different team compositions and level of information. We focus on symmetric positions around the mean - $\theta_i + \theta_j = 100$ and $\theta_i - 50 = 50 - \theta_j$ - covering all the combinations from $(0, 100)$ to $(100, 0)$ with a 0.01 difference in each position by observation.[33] On the level of information, we cover all the values from 0 to 1 with a difference of 0.01 in per observation. It gives a grid of 101×101. Once we have calculated the optimal assignment, we are able to estimate the average profit per round on each point on the grid and to compare across the different organizational structures available. We also are able to determine the optimal team composition and organizational structure given the level of information.

1.6.1 Fixed Positions

We begin with simulations in which managers have pre-selected teams in fixed positions. Figures 1.17 and 1.18 show the average payoffs per round obtained in each combination of team composition and levels of information per organizational structure. Notice that the patterns in both figures are symmetric around the 50-50 teams, those with a distance equal zero. In other words, the expected payoffs per round is almost the same for teams with a distance d or $-d$. Figure 1.17 shows that the positions that maximizes the payoffs per round increment the distance between them as the level of information increases as predicted by the model. On the other hand, Figure 1.18 shows that the positions maximizing the expected profits on the decentralized organization do not depend on the level of information accordingly to the model. Figure 1.17 and 1.18 also shows the range of expected payoffs a manager may obtain on the two types of organizational structures. The participant may obtain an average payoffs per round from $[-0.1, 30.4]$ on the centralized organization while obtaining from $[16.6, 29.7]$. The decentralized organization is a safer option but the centralized organization could do it better when the level of information is good enough.

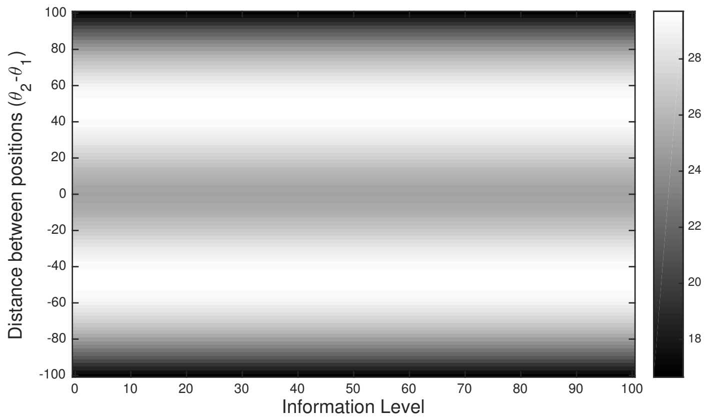
Figure 1.19 identifies the regions where the manager prefers a centralized or a decentralized organization given fixed positions and a level of information. Unlike the case where a manager can choose her team composition, we do not have a threshold level determining which organizational structure is payoff maximizing. Remember that the model predicts a threshold on the level of information of 82% such that for values

[33]Our experimental data suggest that subjects overwhelmingly settle on relatively fixed positions that are symmetric about the midpoint.



Notes. Plots of the average profits of a Monte Carlo simulation with 100 repetitions of 500 rounds given the different team compositions and levels of information on the centralized organization.

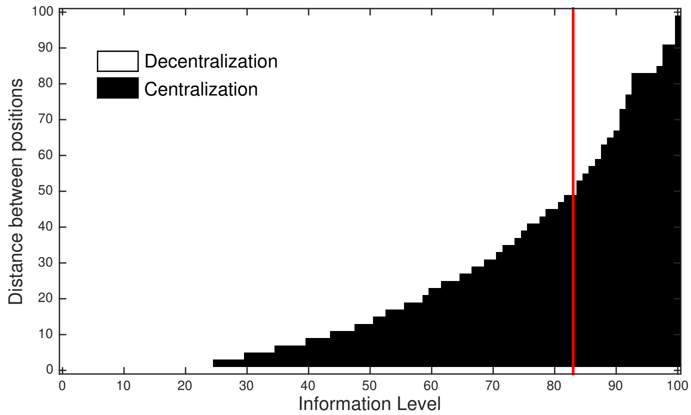
Figure 1.17: Average payoff on the Centralized Organization: Fixed Positions



Notes. Plots of the average profits of a Monte Carlo simulation with 100 repetitions of 500 rounds given the different team compositions and levels of information on the decentralized organization.

Figure 1.18: Average payoff on the Decentralized Organization: Fixed Positions

below that threshold the manager prefers a decentralized organization. Here we observe a convex frontier that separates the region where the decentralized and centralized organizations predominate. The decentralized organization outperforms the centralized organization under more heterogeneous teams. However, this dominance decreases as the level of information increases. Also notice that the decentralized organization dom-



Notes. Plots of the average profits of a Monte Carlo simulation with 100 repetitions of 500 rounds given the different team compositions and levels of information on the decentralized organization.

Figure 1.19: Comparison between Centralized and Decentralized Organizations: Fixed Positions

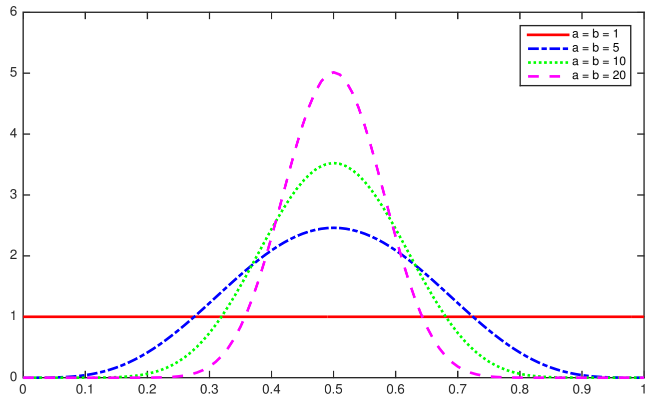
inates for any team composition when the information is below 25%. The observed pattern is in line with the results we have on Figure 1.6. The amount of decentralized rounds reduced as the level of information increases. This suggest that some participants may play as if they have some fixed positions in mind. It is also consistent with the fact that the positions selected are not reactive to the treatment directly and adjust incrementally through the profits obtained period by period.

1.6.2 Alternative symmetric distributions

Are the results exclusively driven by the assumption of the uniform distribution of the tasks? Thankfully, the answer is ”no.” The results are qualitatively similar for unimodal symmetric distributions where the mode is equal to the ex ante expected task. However, a more concentrated distribution around the mode will reduce the threshold on the information level determining the dominance of one or another organizational structure.[34] To analyze how the threshold is affected by the concentration of the distribution, we run additional Monte-Carlo simulations with 100 repetitions of 500 rounds for a group of

[34] By a more concentrated distribution, we refer to the ”peakedness” of the distribution, captured by the excess kurtosis.

symmetric beta distributions. In order to have symmetric beta distributions, we equalize their two shape parameters $\alpha = \beta$. Figure 1.20 plots the histograms for some of the parameters used in the simulation.



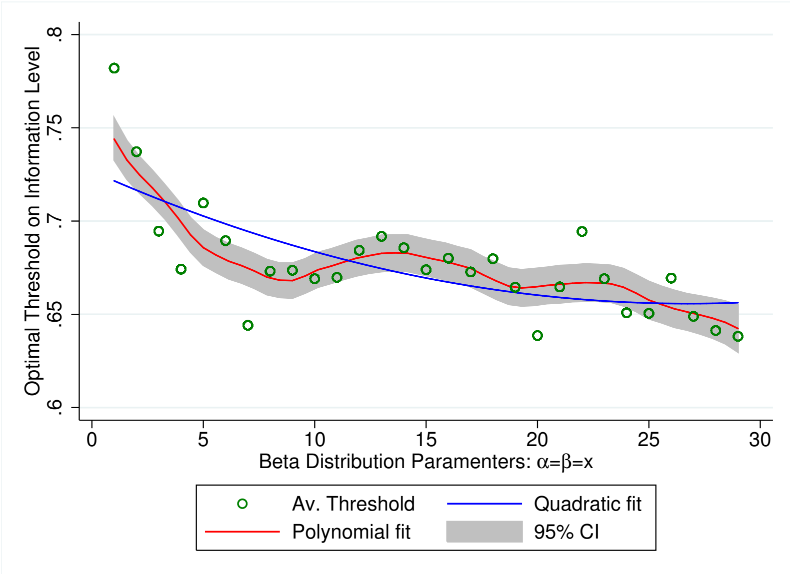
Notes. Different symmetric beta distributions simulated with $\alpha = \beta = k$ where $k \in 1, 5, 10, 20$.

Figure 1.20: Beta simulated distributions

Figure 1.21 plots the results of the simulation. We set our beta parameter value to integers in the interval from $[0, 30]$. As expected we observe that the value of the threshold (at which centralization is optimal) drops as the distribution becomes more concentrated.

1.7 Discussion

In this paper, we use a steady state model to generate testable predictions, but rely on a repeated experimental design in order to give subjects feedback and experience, providing a better test of the model. However, we have not devoted time in the analysis to examine learning, clearly an important issue in this environment. The difficulty is that the game is rather complex, leaving us with an identification problem due to low degrees of freedom. Subjects in the selector stage may be “learning” by changing their organizational structure decision, their team composition, or both.



Notes. Plots of the average profits of a Monte Carlo simulation with 100 repetitions of 500 rounds given the different beta symmetric distributions with $\alpha = \beta = k$.

Figure 1.21: Threshold on the information for different symmetric distributions

A simpler environment would be ideal for addressing how subjects learn in this game. For instance, we could study how subjects learn with respect to team composition by using a between-subjects design. Providing subjects with 40 periods of one organizational structure and one level of information accuracy might be direct enough to confidently say something about learning. While we give repeated rounds with each structure, we limit this to ten rounds each. Alternatively, we could study how subjects learn to play the optimal organizational structure by limiting the team composition choice. In both directions, we could be more confident in our conclusions because managers would only be tasked with a single decision in each period. These are valuable avenues of future research. Moreover, it is important to understand how managers adjust their allocation of decision rights when facing a fixed team composition. Unlike private organizations, new managers in public organizations sometimes cannot change employees. However, they can affect the allocation of decision rights. My hypothesis is that when managers do not have the possibility to select their team composition, they opt for more centralized organization even if it reduces their payments. It could explain the high levels of centralization observed in many public institutions.

Additionally, we are intrigued by the phenomenon we call the loss aversion effect. The complexity precludes a causal explanation for this effect, though again we see this as a direction for future exploration. In particular, it would be insightful to see how much each factor of our decision framework contributes to the effect, and whether the effect may be seen in similar models of organizational structure.

1.8 Conclusion

We study the organizational structure decisions of managers who also have control over their team composition, which we argue provides insight into the complex decision environments commonly faced in firms. We find generally that although our model's predictions are not precisely matched by the experimental data, the theory nonetheless provides intuition for the results obtained.

For instance, we find that the subjects react to the accuracy of information much like the model predicts. While managers too often select centralized decision making, we do see them react to information quality in the correct way. Decentralization rises as information becomes harder to obtain, even though managers have other tools with which to react to scarce information such as team selection.

The experiment confirms that there are more heterogeneous teams chosen in decentralized organizations. However, we find that managers react to negative outcomes by selecting disproportionately homogeneous teams, which is in line with loss averse behavior. In the centralized stage, this effect is significant on the 20% treatment and the reaction allows the participants to get closer to the model predictions. On the other hand, in the decentralized stage, this effect is significant to the 80% treatment but the reaction is against the optimal positions suggested by the model. While more analysis of this loss aversion effect is needed, our study suggest that when managers observe a worker's decision against their interest on previous rounds, they overreact, choosing a disproportionally homogeneous team in the decentralized stage. As uncertainty is reduced, this effect becomes more evident.

The model captures some important characteristics of managerial decision making in firms, and the data suggest that many of the tensions in the model have real impact on behavior. We plan to further utilize this theory to further explore the trade-offs managers must face in both organizational structure and team composition. The findings suggest ways in which firm managers may struggle to allocate decision rights and select their workers, but the model provides valuable insight into how these issues may be overcome.

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Chapter 2

INPUT ALLOCATION, WORKFORCE MANAGEMENT AND PRODUCTIVITY SPILLOVERS: EVIDENCE FROM PERSONNEL DATA

2.1 Introduction

Differences in management practices explain a considerable amount of variation in firms' productivity and performance.[1] 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 [14, 15], Bloom et al. [12, 13]).

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 [5] 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

[1] This paper is coauthored with Francesco Amodio from Universitat Pompeu Fabra.

scheme. As a result, average productivity increases by at least 50% when piece rate pay is introduced. More recently, Mas and Moretti [37] 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 [22]).

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. In other words, if all workers are assigned the same number of hens, an increase in average coworkers' daily output of 500 eggs is associated with a decrease of own output of 150 eggs in the same day. 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 [37], 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 in terms of increased probability of keeping the job decrease for a given worker, and her optimal effort supply falls accordingly.[2]

[2]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

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. The probability for a given worker to keep the job is positively and significantly correlated with own productivity measures. Furthermore, conditionally on the latter, the same probability is positively and significantly correlated with coworkers' productivity as well. In line with the previous results, we find that returns from own productivity in terms of increased probability of keeping the job are systematically lower when coworkers' productivity is higher. Coworkers' productivity thus decreases the optimal amount of effort exerted by the worker, yielding negative production externalities.

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 [34], Falk and Ichino [24], Mas and Moretti [37]). 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. On the contrary, the effect of coworkers' productivity is negative and significant when the same worker is assigned either young or old hens, meaning he is less likely to reach the piece rate threshold. Evidence

framework in Section 2.5.1 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 2.5.2 and Appendix B.3.

thus suggests that monetary incentives push the sign of productivity spillovers towards positive values.

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 cooperative behavior among coworkers. Indeed, workers who are assigned highly productive inputs may benefit from the help of neighboring coworkers, with negative productivity spillovers on the latter. We would expect such cooperative strategy to be more sustainable among friends. The absence of any significant effect in this case speaks against this hypothesis. Moreover, this same result also allows us to rule out that negative spillovers are built in the production function, with their origin being technological in nature. Indeed, if this was the case, there would be no reason to expect the effect to be heterogeneous depending on the status of social relationships among workers.

Causal estimates of productivity spillovers are further validated by several robustness checks. First, we investigate whether variation in the average input quality of workers in non-neighboring production units or different sheds relates systematically to individual productivity. The structure of the production plant is such that workers not located one next to the other cannot observe each other. Therefore, we do not expect to find any significant relationship between the two. We thus frame this empirical exercise as a *placebo test*, which indeed provides non-significant results and estimates close to zero. Second, we replicate our main analysis employing an alternative measure of exogenous input quality, that is, the expected productivity of hens as reported by an independent bird supplier company. The estimates based on this alternative measure match closely the previous ones.

Our case study provides empirical evidence of free riding among coworkers, imputable to the teamwork-type externalities generated by the firm's worker evaluation and termination policy. In this respect, our results add to the literature which investigates the externalities generated by human resource management practices. Bandiera, Barankay and Rasul [5] 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 [9]). Bandiera, Barankay and Rasul [6, 7, 8] 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 [10] 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 [30] 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 [37]. 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 these issues, 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 [30] 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 [26] 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 [4] 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 [19] 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 [28] 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 [21] 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 [36], a number of studies have delved into the empirics of social interactions mechanisms.[3] For example, Ichino and Maggi [31] show evidence of peer effects in absenteeism and shirking behavior in a large Italian firm through exploiting variation in peer group composition induced by workers moving across firm branches. Sacerdote [39] uses instead random assignment of peer college students to dorms and shows evidence of peer effects in academic achievement. An alternative identification approach based on variance decomposition is developed and adopted by Graham [27]

[3]For a recent survey of the empirics of social interactions, see Ioannides and Topa [32] and Blume et al. [17].

in providing evidence of peer effects among students involved in the Project STAR. More recently, a growing number of contributions exploit the variation induced by overlapping peer groups and identify peer effects adopting network-based strategies (Lee [35], Bramoullé, Djebbari and Fortin [18], De Giorgi, Pellizzari and Redaelli [23], Blume et al. [16]).

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 2.2 provides the details of the setting. The data and the relevant baseline statistics are presented in Section 2.3. Section 2.4 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 2.5, together with the corresponding empirical analysis. The impact of monetary and social incentives is discussed in Section 2.6, while Section 2.7 presents the counterfactual analyses of alternative input assignment schedules and dismissal policies. Section 2.8 concludes.

2.2 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 2.1. Each sector is divided into several different long-shaped *sheds*, as pictured in Figures 2.1 and 2.2. 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 2.3.

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.

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

Figure 2.1: One Sector

In particular, they are all of the same age. This is because birds in the same batch are bought altogether when still eggs from an independent bird supplier company. After birth, they are raised in a dedicated sector. The entire batch is then moved to production when hens are around 20 weeks old, and discarded altogether when reaching around 80 weeks of age. The productive life of laying hens is thus approximately 60 weeks long. During that time, the batch is always assigned to the same production unit. The position of the worker is fixed over time as well. Worker's main tasks are: (i) to collect and store the eggs, (ii) to feed the hens and (iii) to maintain and clean the facilities.[4] Egg production establishments in developed countries are typically endowed with automatic feeders and automated gathering belts for egg handling and collection.[5] The production

[4]The worker's typical daily schedule is reported in Table B.1 in the Appendix B.1. Figure B.1 in the Appendix B.2 shows the distribution of the estimated worker fixed effects as derived as described at the end of Section 2.4. The variance of the distribution is indicative that, conditional on input quality, workers can have a substantial impact on productivity.

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

Notes. The picture of a shed in the plant under investigation.

Figure 2.2: Sheds

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 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 2.3, 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

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

Figure 2.3: Production Units

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.

2.3 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. It follows that each production unit hosted an average of 1.73 batches and 1.01 workers over the sampling 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.[6] 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 2.1. 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

[6]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 2.4. In particular, results from Table 2.5 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.

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.

Table 2.1: Summary Statistics

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. 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. Derived output quality measures include the fraction of good, broken and dirty eggs over the total. On average, 86% of eggs produced by a production unit in a day are labeled as good, and are thus ready to go through packaging. 6% of eggs on average are instead labeled as dirty. Workers can turn a dirty egg into a good egg by cleaning it. Finally, an average fraction of 0.1% of hens in a batch die on a daily basis.

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

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] 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 2.6.

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

2.4 Empirical Analysis of Productivity Spillovers

2.4.1 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 2.4 plots the chosen productivity measure - average daily number of eggs per hen - against hens' age in weeks. The figure 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 2.4 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]

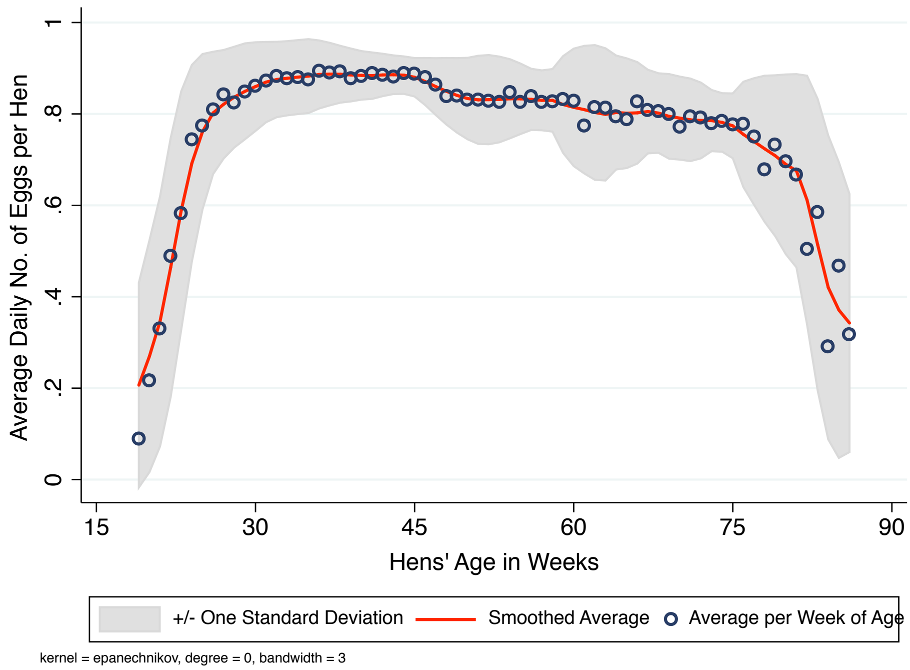
Hens' age exogenously shifts input quality and thus productivity as measured by daily output y_i. This source of variation can be exploited in order to identify productivity spillovers. Specifically, we start by considering the following regression specification

$$y_{igt} = \varphi + \gamma\,\bar{y}_{-igt} + \alpha\,age_{igt} + \beta\,age^2_{igt} + \sum_{s=t-3}^{t-1} \lambda_s\,food_{igs} + \varepsilon_{igt} \qquad (2.1)$$

where y_{igt} is the daily number of eggs per hen collected by worker i in shed g on day

[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 2.1, 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.



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

Figure 2.4: Hens' Age and Productivity

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 2.4.[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 previous

[10] In Section 2.4.2, we also use week-of-age dummies in order to better fit the productivity-age profile shown in Figure 2.4. 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.

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 [36].[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 [36], Blume et al. [17]). 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, as reported in the first

[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 [36] 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 [18], Blume et al. [17], Angrist [2]).

	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 [11]). Regression results in the bottom panel are based on Guryan, Kroft and Notowidigdo [28] 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 2.2: Coworkers' and Own Hen's Age: Conditional Correlation

column in the top panel of Table 2.2. 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 production units have approximately the same age. However, there is still residual variation to exploit. The second column in the top panel of Table 2.2 shows how the same correlation between coworkers' and own hens' age falls to zero when computed conditional on the full set of shed-week fixed effects.[13] 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. This same hypothesis can be tested by means of the regression specification proposed by Guryan, Kroft and Notowidigdo [28], 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 shown in the bottom panel of Table 2.2. Standard errors are clustered along the two dimensions of shed and day. According to our results, the H_0 cannot be rejected.

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.[14] Nonetheless, before

[13]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, a problem already noted by Bayer, Ross and Topa [11] and discussed extensively in Guryan, Kroft and Notowidigdo [28] and Caeyers [20]. The bias in this case is of the same nature as the so-called Nickell-Hurwicz bias arising in fixed effects panel estimations with short time series (Nickell [38]). In order to overcome this problem, when estimating conditional correlations we follow Bayer, Ross and Topa [11] 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]Several contributions in the literature exploit within-group random variation in peer characteristics in order to identify peer effects (see for instance Sacerdote [39], Ammermueller and Pischke [1], Guryan, Kroft and Notowidigdo [28]). They aim to find evidence of a systematic relationship between own outcomes and peer predetermined characteristics, leaving aside the issue of differentiating between *endogenous* and *exogenous* peer effects (Manski [36]). In this context, the parameter γ can be correctly identified

showing the results, it is important to understand whether 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.[15]

2.4.2 Baseline Results

The first set of regression results is reported in Table 2.3. In the first column, the daily average number of eggs per hen collected by the worker is regressed over the age of hens in weeks and its square. The full set of day fixed effects are included as well. The proposed specification yields a quadratic fit of the dependent variable as a function of hens' age which is consistent with the evidence in Figure 2.4.[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 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.

The average age of hens assigned to coworkers in neighboring production units is included in Column 4 of Table 2.3, together with its square.[17] Consistently with the con-

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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.

[15] 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.3 of Appendix B.2.

[16] As previously mentioned, in Section 2.4.2 we also use hens' week-of-age dummies in order to better fit the productivity-age profile.

[17] Caeyers [20] shows that no mechanical downward bias arises in the estimation of the parameters of

	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.

Table 2.3: Own and Coworkers' Hens' Age and Productivity

ditional correlation result in Table 2.2, 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]

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

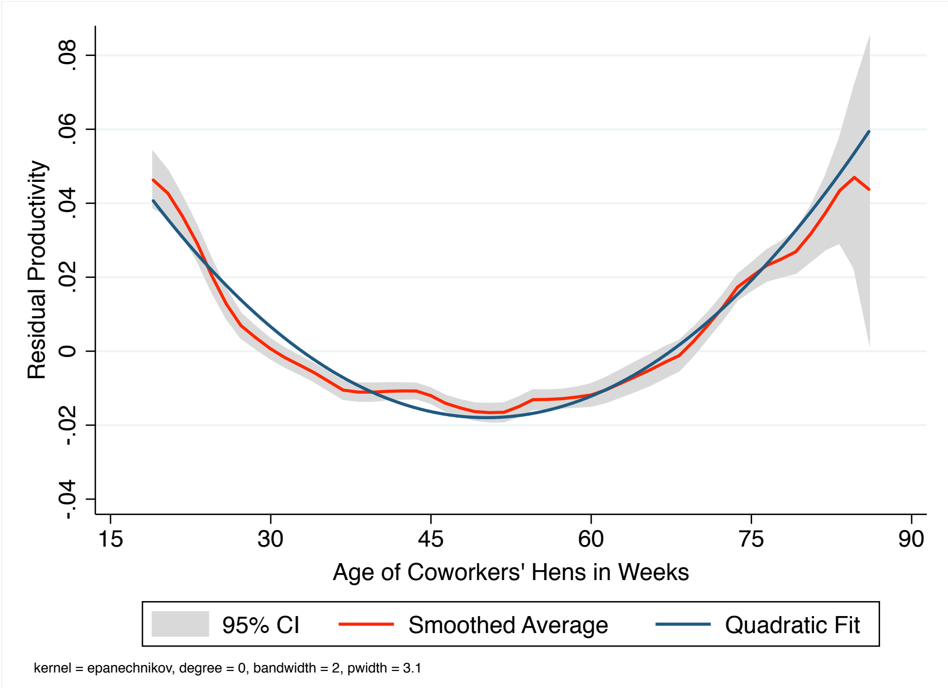
Any systematic relationship between the average age of coworkers' hens and own productivity can thus be interpreted as reduced-form evidence of productivity spillovers. The corresponding coefficients are highly significant and opposite in sign with respect to the ones of own hens' age.[19] This result is confirmed in Column 5 of Table 2.3, 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 2.5 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 2.3 already suggest the

its square separately as controls one by one, as shown in Table B.2 in the Appendix B.2.

[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 [20] shows that no mechanical downward bias arises in the estimation of the parameters of interest in the specification of interest using 2SLS.

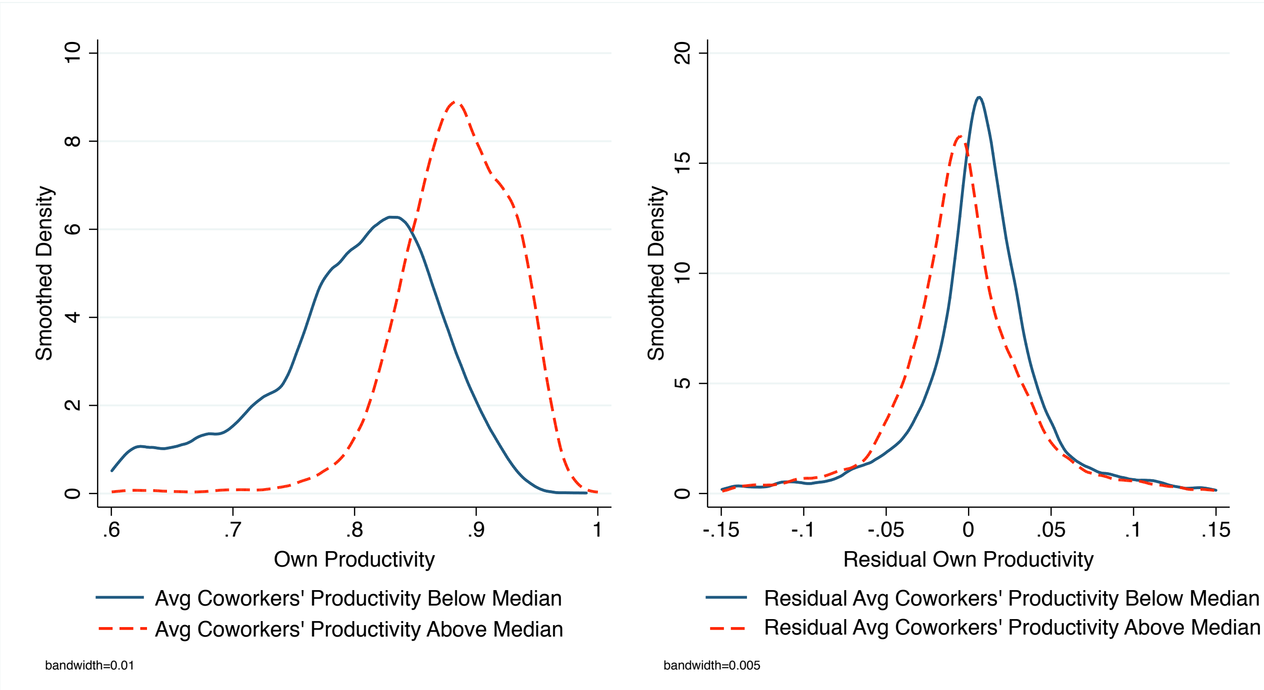


Notes. Once own hens' age, day and shed-week fixed effects are controlled for, residual productivity is plotted against the age of coworkers' hens in weeks. Productivity is measured as the average daily number of eggs per hen collected by the worker. Recall that hens in a given batch are all of the same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

Figure 2.5: Residual Productivity and Age of Coworkers' Hens

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.

As a further attempt to explore the relationship between the productivity of neighboring coworkers, Figure 2.6 plots the distribution of own productivity separately for those workers whose coworkers' average productivity is above or below the median in the same day. Productivity is still measured by the daily average number of eggs per hen collected by the worker. The left figure shows the resulting distributions for unconditional productivity. The distribution for workers whose coworkers are highly productive is found to be on the right of that for workers whose coworkers are of low productivity. This is consistent with the unconditional positive correlation result on own and coworkers' hens age as reported in Table 2.2. Nonetheless, once shed-week averages are netted out, the picture reverses. The distribution of residual productivity for workers whose coworkers have residual average productivity above the median is now on the left of that for workers in the other group, consistently with the negative correlation results in Table 2.3.



Notes. The figure plots the distribution of own productivity separately for those workers whose coworkers' average productivity is above and below the median. Productivity is measured as the average daily number of eggs per hen collected by the worker. The left figure refers to unconditional productivity. The right figure plots instead the distributions of residual productivity net of shed-week fixed effects. While own and coworkers' productivity appear to be positively correlated, conditioning on the full set of shed-week fixed effects yields the opposite result.

Figure 2.6: Own and Coworkers' Productivity

The first column in Table 2.4 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 together are thus relevant in inducing variation in the regressor of interest.[21] More

[21]The *p-value* from the Sargan-Hansen test of overidentifying restrictions is higher than 0.10. We

importantly, the 2SLS estimate $\hat{\gamma}_{2SLS}$ is negative and significant at the 1% level. OLS and 2SLS estimates are of very similar magnitude. One possible explanation for this result is that the different sources of bias of OLS estimate in this case work both in the positive (sorting, correlated effects) and negative direction (reflection, mechanical bias from the inclusion of group fixed effects as discussed in Guryan, Kroft and Notowidigdo [28] and Caeyers [20]), 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

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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.

	Daily Number of Eggs per Hen, y_i			
	(1)	(2)	(3)	(4)
	OLS	2SLS	2SLS	2SLS
Coworkers'	-0.29539***	-0.30258***	-0.28877***	-0.29019***
Eggs per Hen, $\bar{y}_{-i}$	(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.

Table 2.4: Coworkers' and Own Productivity

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 2.4 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 2.5. 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 2.5, 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

	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.

Table 2.5: Feeding Effort and Output Quality

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 2.5 suggest coworkers' productivity to negatively affect not only own output but its quality as well.

2.4.3 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 their productivity. Column 1 of Table 2.6 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

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

[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 2.5.

	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 2.4.3. 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.

Table 2.6: Robustness Checks and Effect Heterogeneity

identification strategy, as shown in Column 3 of Table 2.6, 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

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.

with a 29% decrease in own output. Finally, in Column 4 of Table 2.6, 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 [5] and Mas and Moretti [37], 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 separately and results reported in Columns 5 and 6 of Table 2.6. 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.

[25]We also perform two additional robustness checks. First, we address the identification concerns in Angrist [2] 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.3 in the Appendix B.2.

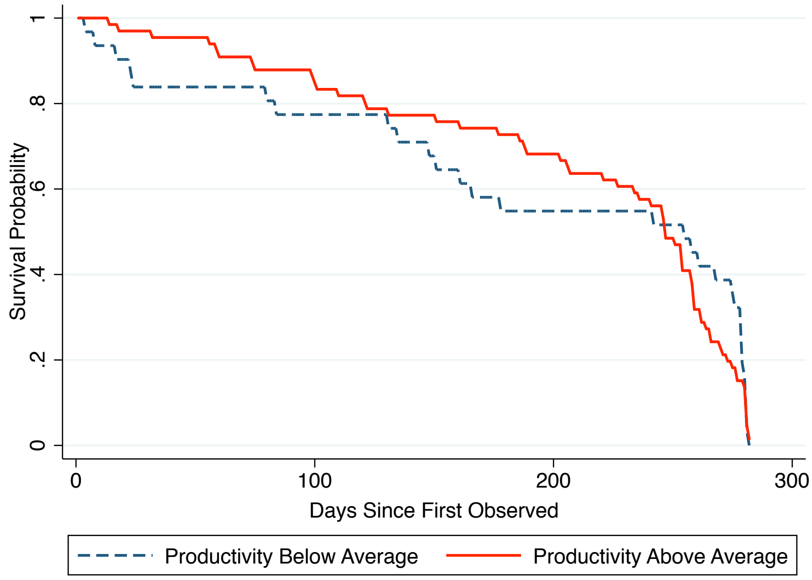
[26]The distribution of workers' ability is shown in Figure B.1 in the Appendix B.2.

2.5 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 [40]).

Figure 2.7 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 2.8 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. All this

[27] See Section 2.6.2 and Table 2.8 for more detailed information on the wage schedule of workers at the firm. Average and minimum wage data are from the World Bank.



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.

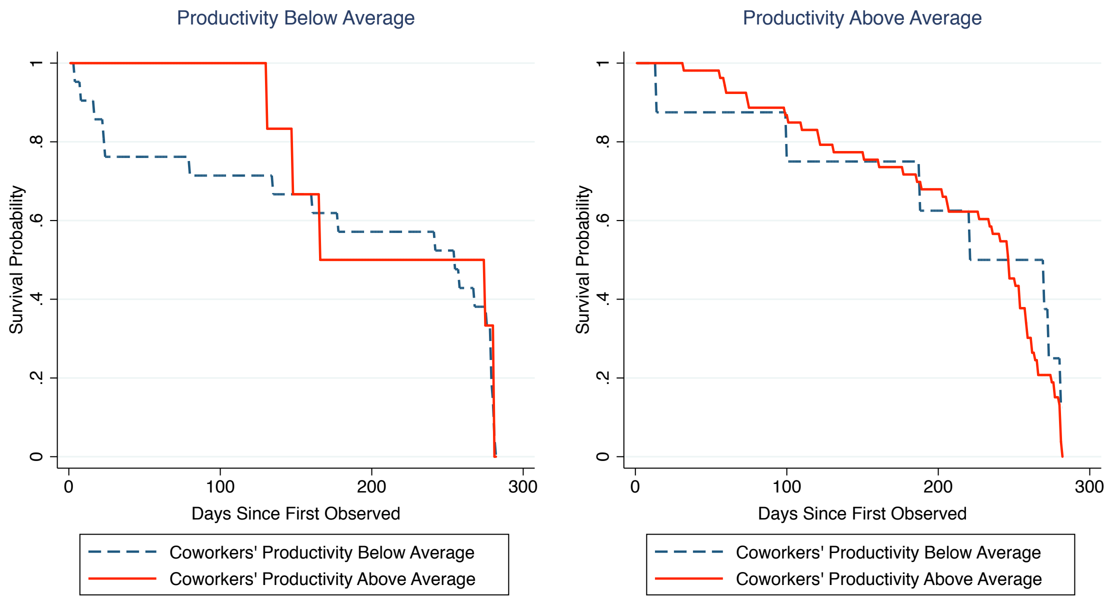
Figure 2.7: Survival Probability and Productivity

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.

2.5.1 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

$$y_i = f(e_i, s_i) \tag{2.2}$$



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.

Figure 2.8: Survival Probability and Coworkers' Productivity

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 [37], 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'

[28]One specific example is given in Appendix B.3, where we also consider the possibility for the principal to net out observable input characteristics in deriving a signal of worker's exerted effort.

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 [37], we do not rely on any specific functional form, and only assume $q_1(\cdot) > 0$ and continuously differentiable, $q_{11}(\cdot) \leq 0$ and that $q_{12}(\cdot)$ exists. As shown later, this allows to take into consideration several alternative termination policies.

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

$$\max_{e_i} U(\omega)\, q(y_i, \bar{y}_{-i}) - c\frac{e_i^2}{2} \tag{2.3}$$

Taking the corresponding first order condition yields

$$U(\omega)\, q_1(y_i, \bar{y}_{-i})\, s_i = ce_i \tag{2.4}$$

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

$$\frac{\partial e_i^*}{\partial \bar{y}_{-i}} = \frac{U(\omega)\, q_{12}(y_i, \bar{y}_{-i})\, s_i}{c - U(\omega)\, q_{11}(y_i, \bar{y}_{-i})\, s_i^2} \tag{2.5}$$

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, $Q_i = q\left(\alpha y_i - \beta \bar{y}_{-i}\right)$ 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 $Q_i = q\left(y_i + (N-1)\bar{y}_{-i}\right)$. This implies $q_{12}(\cdot) < 0$. The worker's optimal effort level will thus fall with an increase in coworkers' average output. 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 [37] 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.

2.5.2 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 2.8 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

[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.

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

defined by

$$\frac{1 - q(t)}{q(t)} = \frac{h(t)}{1 - h(t)} = \exp\{\ \gamma_t + \alpha\, y_{it} + \beta\, \bar{y}_{-it} + \kappa\, y_{it} \times \bar{y}_{-it}\ \} \tag{2.6}$$

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 2.7. 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 [41] and adopt a two-stage residual inclusion (2SRI) approach. As before, we use the age of coworkers' hens $\overline{age}_{-it}$ and its square as instruments for coworkers' productivity $\bar{y}_{-it}$, and their interaction with own productivity as instruments for $y_{it} \times \bar{y}_{-it}$. Identification of the effect of coworkers' productivity on termination probabilities is here achieved through exploiting the variability induced by the age of coworkers' hens, consistent with the previous analysis.

Table 2.7 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

[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.

	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 [41]).

Table 2.7: Termination Policy

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 B.3, where we present a modified version of the conceptual framework in Mas and Moretti [37]. 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 [33], Gifford [25], Hirshleifer and Teoh [29]). 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 2.4 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 2.6 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.

2.6 Monetary and Social Incentives

2.6.1 Extended Conceptual Framework

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

[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.

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' 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 [34], 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 [24] and Mas and Moretti [37] 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

$$\max_{e_i} U(\omega)\, q(y_i, \bar{y}_{-i}) - c\frac{e_i}{2}\,(e_i - \lambda\, \bar{y}_{-i}) \tag{2.7}$$

where $\lambda > 0$ is a generic parameter capturing the intensity of peer pressure mechanisms. Deriving the corresponding first order condition and applying the implicit function theorem yields

$$\frac{\partial e_i^*}{\partial \bar{y}_{-i}} = \frac{U(\omega) q_{12}(\cdot) s_i + \lambda \frac{c}{2}}{c - U(\omega) q_{11}(\cdot) s_i^2} \tag{2.8}$$

While the denominator of the above remains unchanged with respect to the corresponding result in the original formulation, the numerator is now ambiguous when $q_{12} < 0$. 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.

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

$$\max_{e_i} (F + \kappa y_i) q(y_i, \bar{y}_{-i}) - c\frac{e_i^2}{2} \tag{2.9}$$

The corresponding first order condition is now

$$(F + \kappa y_i)q_1(\cdot)s_i + \kappa q(\cdot)s_i = ce_i \tag{2.10}$$

Compared to the fixed-wage case, piece rate incentives provide extra motivation for effort, as captured by the second term on the left-hand side. In particular, notice that monetary incentives are leveraged by the probability $q(\cdot)$ of keeping the job. Applying the implicit function theorem we can see how optimal effort responds to coworkers' productivity in this case

$$\frac{\partial e_i^*}{\partial \bar{y}_{-i}} = \frac{(F + \kappa y_i)q_{12}(\cdot)s_i + \kappa q_2(\cdot)s_i}{c - (F + \kappa y_i)q_{11}(\cdot)s_i^2 - 2\kappa q_1(\cdot)s_i^2} \tag{2.11}$$

Provided that c is high enough, the denominator of the above expression is positive.[33] 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' productivity if the second term in the numerator is high enough. In other words, if total output matters to some extent, coworkers' productivity increases the probability of keeping the job. Even if this lowers the marginal impact of own productivity on the probability of keeping the job, it leverages the power of monetary incentives, as these are earned only if the job is kept. The latter effect may dominate the former, yielding positive productivity spillovers.

2.6.2 Empirics

The setting under investigation carries with it sufficient variation in both the payment schedule and the social relationships among coworkers. Such variation can be exploited in order to formally test for the impact of both monetary and social incentives as derived above.

We start by providing additional information about the workers' pay schedule. 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

[33] 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 $s_i, y_i, \bar{y}_{-i}$.

in the number of boxes of eggs collected by the worker in a randomly chosen day within the two weeks. Specifically, wage is calculated according to the following formula

$$w_i = \omega \; + \; \delta \; + \; \max \{ \, 0 \, , \, \gamma \times [\, 2Y_i - r \,] \, \} \tag{2.12}$$

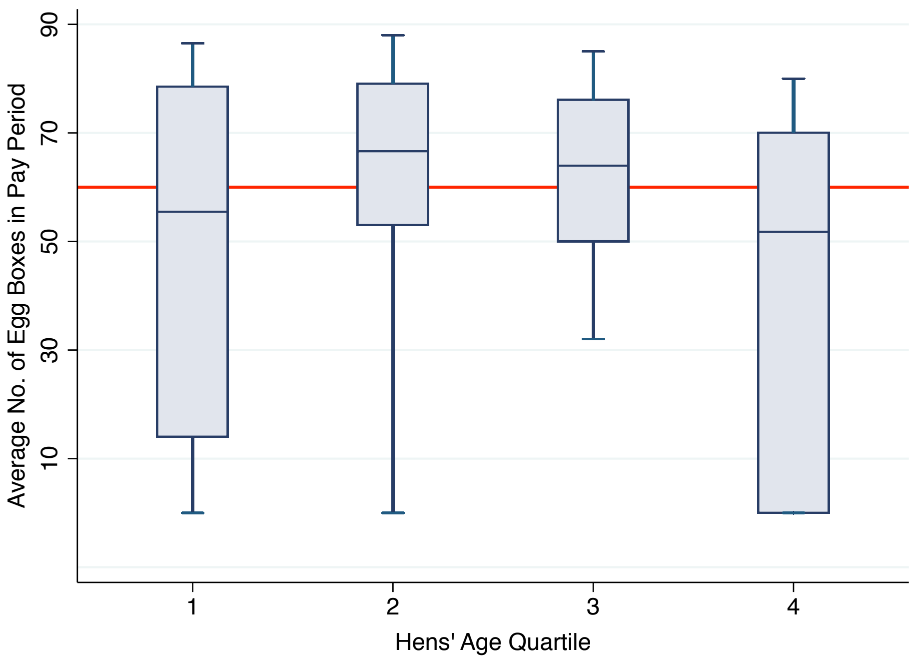
where ω is the base pay and Y_i is the amount of boxes of eggs collected by the worker in the randomly chosen day. This quantity is multiplied by 2 and, if the resulting quantity exceeds a given threshold r, a piece rate pay γ is awarded for each unit above the threshold. On top of base pay, almost all workers are awarded an extra amount δ. Table 2.8 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). The bonus component is thus on average equal to 15% of the base pay. As a result, average total pay in the two-weeks period is equal to the equivalent of 220 USD.

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 2.6 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 2.8: Pay: Summary Statistics

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 2.9 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.



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

Figure 2.9: Hens' Age and Number of Egg Boxes

Table 2.9 shows the average base pay, bonus pay and total pay for the average worker across the assigned hens' age distribution, confirming the existence of a strong relationship between hens' age and bonus pay. Notice that small variations in base pay are observed across productivity categories. Base pay can indeed still vary with workers' age, tenure and base contract. Nonetheless, most of the variation in total pay is due to variations in the bonus pay component. Finally, Figure 2.10 shows the distribution of bonus pay for workers in each quartile of the assigned hens' age distribution. Consistently with the previous description of the pay scheme, a more pronounced peak is observed around the value of δ in the distribution for workers whose assigned hens are either young or old, meaning that few of them make it to the threshold and gain the piece rate component of 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

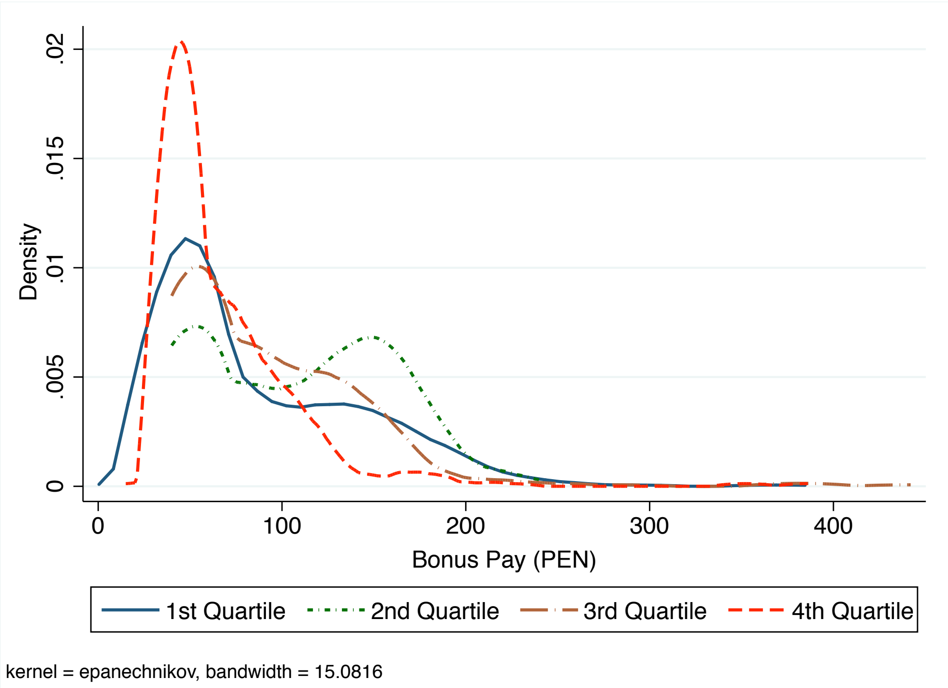
Notes. Average bonus pay per quartiles of hens' age distribution. 1 PEN = 0.38 USD (June 30, 2012).

Table 2.9: Hens' Age and Bonus Pay

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

$$\begin{aligned} y_{igwt} \;=\; & \varphi_{gw} + \textstyle\sum_d \psi_d \, D_{digwt} \\ & + \textstyle\sum_d \left\{ \gamma_d \, \bar{y}_{-igwt} + \alpha_d \, age_{igwt} + \beta_d \, age^2_{igwt} \right\} \times D_{digwt} \qquad (2.13) \\ & + \textstyle\sum_{s=t-3}^{t-1} \lambda_s \, food_{igsw} + \mu_{igwt} \end{aligned}$$

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 instruments for the endogenous interaction variables $\bar{y}_{-igwt} \times D_d$.[34]



Notes. The figure plots the distribution of bonus pay for workers in different quartiles of the hens' age distribution. A more pronounced peak can be observed in the distribution of workers whose assigned hens are either young or old, and hence less productive. The first peak corresponds to the value of the fixed component δ of bonus pay. Density at this value is higher for workers whose assigned hens are in the 1st or 4th quartile of the hens' age distribution, meaning of low productivity. 1 PEN = 0.38 USD (June 30, 2012).

Figure 2.10: Productivity and Bonus Pay

We first focus on monetary incentives and define two categories according to the

[34]We also estimate the main regression specification using 2SLS separately for each subsample as identified by the dummy D_d. Results are shown in Table B.4 in the Appendix B.2. 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.

distribution of assigned hens' age. As previously shown, 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 2.1, 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 2.10 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 [3]), 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.

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 2.1, 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 2.10.[35] Productivity spillovers are estimated to be negative and significant only for those workers who do not work along friends. Consistently with the peer pressure argument outlined before, a positive point estimate is instead found for the coefficient of coworkers' productivity when the worker recognizes

[35]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.

	Daily Number of Eggs per Hen, y_i				
	(1)	(2)	(3)	(4) High Prod. Age	(5) Low Prod. age
$\bar{y}_{-i}$ $\times$ High Productivity Age	-0.09785				
	(0.3148)				
$\bar{y}_{-i}$ $\times$ Low Productivity Age	-0.21834**				
	(0.1071)				
$\bar{y}_{-i}$ $\times$ Friend		0.22713			
		(0.1747)			
$\bar{y}_{-i}$ $\times$ No Friend		-0.43580**			
		(0.2104)			
$\bar{y}_{-i}$ $\times$ Experienced			-0.60567***		
			(0.1189)		
$\bar{y}_{-i}$ $\times$ Not Experienced			0.23650		
			(0.1587)		
$\bar{y}_{-i}$ $\times$ Low Age Difference				-0.13943	-0.38903
				(0.4793)	(0.3628)
$\bar{y}_{-i}$ $\times$ 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.

Table 2.10: Incentive Heterogeneity

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.[36]

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 2.1. Estimation results are shown in Column 3 of Table 2.10. 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.[37]

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

[36]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.

[37]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 2.10 is driven by experienced workers helping less experienced neighboring coworkers. Additional results are available upon request.

should expect the negative effect of coworkers' productivity to be the highest in magnitude when the scope of free riding is the widest. This corresponds to the situation in which a given worker is assigned lowly productive hens while coworkers are assigned highly productive ones. The size of the effect should then be lower when both workers are assigned lowly productive hens. The same magnitude should be even lower when both workers are assigned highly productive hens, and the lowest when the worker is assigned highly productive hens and his coworkers are assigned lowly productive ones. Evidence from Column 5 and 6 is supportive of this hypothesis. The effect is only statistically significant when workers' hens are lowly productive (i.e., drawn from the first or fourth quartile of the hens' age distribution) and the absolute difference in age with coworkers' hens is high, meaning coworkers' hens are more likely to be in their high productivity age. Point estimates are ordered as suggested above, even if none of the three other 2SLS estimates is statistically significant.

2.7 Counterfactual Policy Analysis

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

$$\frac{U(\omega)}{c}\, q_1(y_i, \bar{y}_{-i})\, s_i = e_i \tag{2.14}$$

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

$$\ln y_i = \ln \frac{U(\omega)}{c} s_i^2 + \ln q_1(y_i, \bar{y}_{-i}) \tag{2.15}$$

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:

$$\tilde{q}(y_{it}) = \alpha_0 + \alpha_1\, y_{it} + \alpha_2\, y_{it}^2 \tag{2.16}$$

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

$$\ln y_{it} = \ln \frac{U(\omega)}{c} s_{it}^2 + \ln(\alpha_1 + 2\alpha_2\, y_{it}) \tag{2.17}$$

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

$$\ln y_{it} = \ln U(\omega) + \ln s_{it}^2 + \ln \hat{q}_{1,it} - \ln c_i \tag{2.18}$$

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

$$\ln y_{it} = \alpha + \psi_{wi} + \beta\, \ln \hat{q}_{1,it} + \theta_i + \varepsilon_{it} \tag{2.19}$$

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

$$\widehat{\ln y_{it}} - \hat{\beta}\ \ln \hat{q}_{1,it} = \hat{\alpha} + \hat{\psi}_{wi} + \hat{\theta}_i = \hat{m}_{it} \tag{2.20}$$

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}

$$\ln y_{it} = \hat{m}_{it} + \ln(\alpha_1 + 2\alpha_2\ y_{it}) \tag{2.21}$$

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 2.11 shows counterfactual productivity gains and losses as predicted under the alternative termination policy, following the procedure described above. For each parameter values, each entry shows the simulated percentage change in productivity as measured by average daily number of eggs per hen collected by the worker over the period. The table also reports 95% confidence intervals as computed by repeating the above estimation procedure 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%. A visual representation of such gains can be find in Figure 2.11, which plots the smoothed average of daily productivity values over time in the sampling period. The continuous line reports the smoothed average of actual daily productivity, while the dashed line shows its value as predicted under $\alpha_1 = 5$ and $\alpha_2 = -1$.

2.7.2 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 realloca-

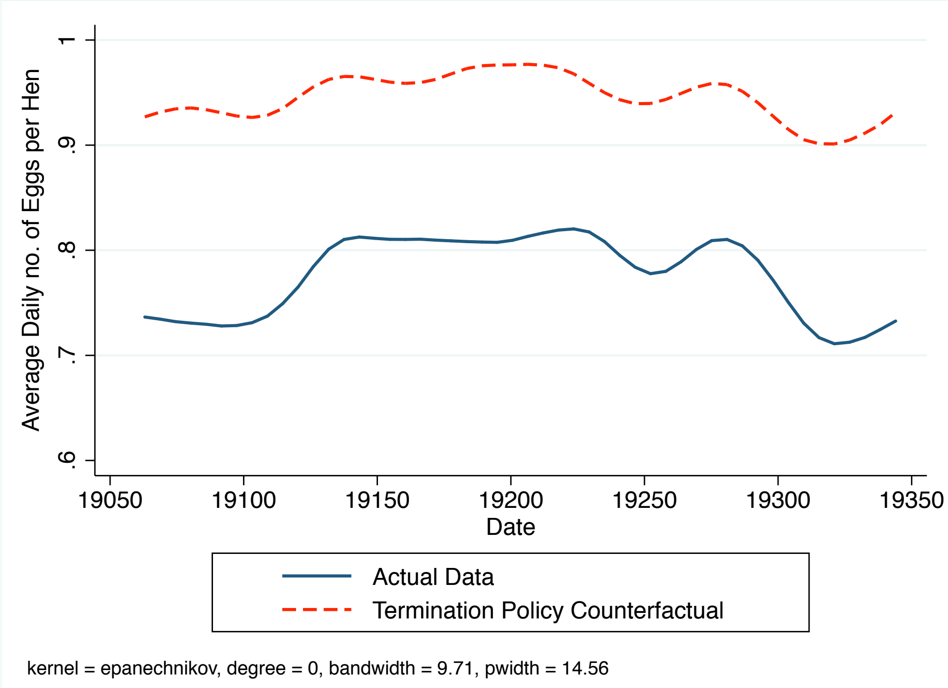
		α_2				
		-0.25	-0.5	-0.75	-1	-1.25
α_1	2	16.66 [13.62;18.11]	1.75 [-2.65;4.47]	-15.91 [-19.10;-14.05]	-28.33 [-30.72;-26.93]	-37.52 [-39.38;-36.42]
	3	20.06 [19.17;20.86]	19.39 [18.45;20.30]	18.06 [15.72;19.26]	7.50 [3.92;9.60]	-6.28 [-9.07;-4.63]
	4	21.45 [20.67;22.19]	21.11 [20.32;21.86]	20.69 [19.89;21.45]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

Notes. The Table shows productivity gains and losses from counterfactual termination policy as discussed and implemented in Section 2.7.2. 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.

Table 2.11: Termination Policy Counterfactual: Results

tion 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.

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 2.12

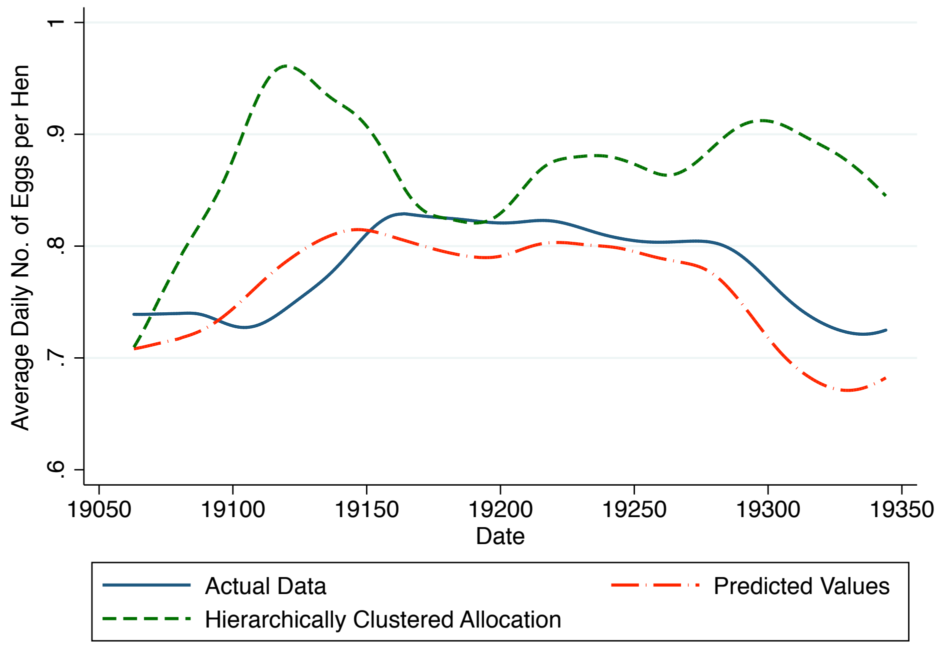


Notes. The figure plots the true and counterfactual average worker's productivity over time in the period under investigation. Counterfactual productivity estimates are derived under an alternative termination policy which does not carry externalities among coworkers, as explained in full details in Section 2.7.2 (parameter values $\alpha_1 = 5$ and $\alpha_2 = -1$). Average counterfactual productivity is always higher than the actual one.

Figure 2.11: Termination Policy Counterfactual

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

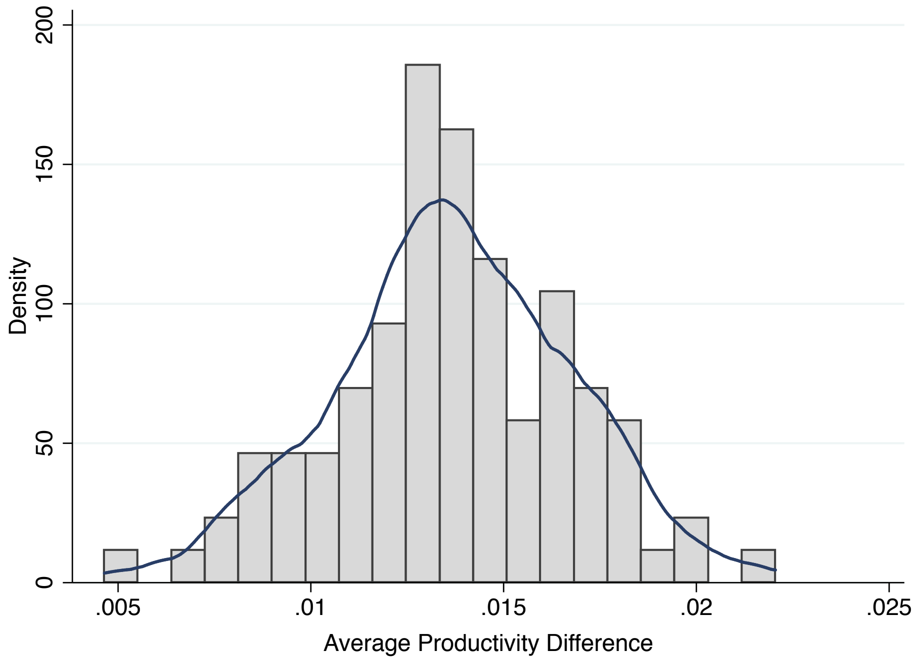


Notes. The figure plots the true, predicted and counterfactual average worker's productivity over time in the period under investigation. Predictions are derived starting with the batches in production in the first week of the sample, and simulating their age profiles over the period, assuming that hens 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.

Figure 2.12: Input Allocation and Productivity

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 2.12. 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. Figure 2.13 shows the distribution of the average productivity difference throughout the sample period between the actual productivity and the productivity estimated under 100 alternative scenarios of this kind, where hen batches are randomly allocated to production units. The difference is always positive, with the average being equal to 0.0136 and significantly different from zero. 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.



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.

Figure 2.13: Random Input Allocation and Productivity

2.8 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 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.

Thanks to the peculiarities of the setting under consideration, 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. We here focus on the way the management informs its decisions on whether and who to dismiss as the mechanism behind the negative productivity spillovers we find, and how incentive provision can neutralize them. Nonetheless, the same logic can be applied in the empirical study of other types of spillovers. 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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Chapter 3

MULTIPLE PERFORMANCE MEASURES IN A MULTITASKING CONTEXT: ON THE DESIGN OF INCENTIVE

3.1 Introduction

One of the main concerns of firms is to provide the right incentive to their workers.[1] However, the incentive design crucially depends on the type of information available. When firms are not able to observe workers' actions, they commonly use variable payments as a function of different performance measures generated on the productive process. Theoretically, a well designed incentive scheme depends on a portfolio of performance measures that are informative about workers actions and allows the firm to align workers preferences with the firm's objective (Baker [1]; Datar, Kulp and Lambert [12]; Feltham and Xie [15]).[2] Finding one performance measure satisfying both characteristics is unusual. Baker [1] suggests that performance measures tend to show a

[1]The percentage of employees exposed to incentive pay schemes ranges from 10-15% in some European countries to over 40% in Scandinavian countries and US (Bryson [7]).

[2]On one hand, informativeness about workers actions is a concept related to noise of the portfolio of performance measures that the workers can not control. It determines how much risk workers have to bear. On the other hand, the level of alignment between two measures capture how similar are the marginal contributions of workers' actions over those measures.

negative relationship between their levels of informativeness about workers actions and their alignment with the firm's objective.[3] Thus, a portfolio of performance measures could balance those different characteristics and provides more appropriate incentives. If a measure is informative but not aligned, workers effort maximizes the performance measure but not the firm's objective. On the contrary, if a measure is aligned but not informative, workers effort is irrelevant, no incentive is provided.

Payment contracts based on multiple performance measures are far from uncommon. Gibbs et al. [18] show on a survey to auto dealership managers that 25% of them had two or more performance measures on their compensation. Also, there are different governmental organizations using multiple performance measures to evaluate how to allocate their funds across public institutions (Courty and Marschke [10]). However, beyond these examples, there is a lack of empirical analysis understanding if firms and organizations use multiple performance measures appropriately. This paper is a contribution on this direction. Studying an incentive scheme change in a leading egg producing company in Peru, I quantify the potential efficiency gains of incentive schemes using a well designed portfolio of performance measures. It also allows me to explore the role of the worker's risk aversion, the relative prices of output/input measures and performance thresholds activating the variable payment.

In this company, workers' fortnight payment consists in a fixed wage - determined by the number of days worked – and linear payment on performance – a variable payment. The variable payment is activated when the performance measures are above a performance threshold determined by the firm. The main tasks of each worker are to collect the eggs, feeding the hens and maintain the installations. Before March 2012 the variable payment depends on two different measures: 1) total boxes of eggs collected per worker – output produced; and 2) sacks of food distributed among hens per worker – input used. After March 2012 the variable payment just depends on the former measure. An important characteristic of the previous measures is that total boxes of eggs produced per worker is more aligned with firm's objective than the other measure, but

[3] Loan officers contracts may depend on the amount of lending money or on the profitability of the loan. The first measure is less aligned with the bank performance but it is more informative about the effort of the loan officers, while in the second measure the opposite happens. Other examples can include the use of group measures versus individual measures. Firms want to maximize the performance of the group but the individual measure is more informative about workers effort. Finally, we can consider situations where a worker produced an item using different amount of inputs. The input measure captures better how much effort workers exert, but the output is more aligned with firm's objective.

it depends in several variables the workers can not control. On the other hand, the sacks of food distributed are more informative about the worker's feeding effort, but it is less aligned with the firm's objective. Why does the firm change the contract? What could we learned respect to the appropriate incentive design?

Unlike previous studies comparing piece rate pay schemes against fixed wages, I observe two piece rates pay schemes depending on different performance measures. It provides me with the basic framework to analyze the use of different performance measures together. I have access to daily information per worker of the main variables in the productive process during the years 2011 and 2012.[4] Moreover, the firm's characteristics and how the incentive scheme was implemented allow me to identify the impact of the new contract on workers' behavior. First, no other changes on the production environment took place during this period. Second, each worker has her own group of hens assigned. Once assigned, a worker remains with the same group of hens until they are dismissed.[5] Coworkers' actions have not direct impact on the variables affecting workers' payment. Third, workers have a fixed schedule for each task that eliminates effort substitution among them. Fourth, I identify periods with high stability on workers' actions where I compare the same subset of workers before and after the incentive scheme.[6] Using those stable periods as the reference for the analysis I capture the optimal actions of the workers in steady state avoiding uncontrolled dynamic effects. Also, comparing the same subset of workers before after I avoid confusing factors as a workforce recomposition effects.

In this paper, I structurally estimate the main parameters of an extended multitasking model based on Baker [1]. In the model, workers have two tasks and the firm observes two performance measures. Those performance measures linearly depend on the tasks. As in our case of study, I assume that one performance measure - the output measure - is perfectly aligned with the firm's objective. Unlike previous models, I assume workers have limited liability and they are ex-post heterogeneous on their marginal cost of effort. After workers sign the contract, they realize their marginal cost but the firm cannot

[4]The information is from one specific sector of the company. This sector counts with 76 workers and 850 000 hens per day on average.

[5]The plant is divided in production units. Each production unit has a worker and a group of hens. The hens assigned to a production unit have similar ages. Workers remain in the same production unit with the same group of hens until they are dismissed.

[6]Those stable periods have 170 days consisting on periods between June and December for the years 2011/2012. We have observations before and after for 63 of the workers, 85% of the daily labor force.

observe this. It generates ex-post asymmetric information between the firm and the workers.[7] In this context, I evaluate the optimal linear contract as a function of the performance measures. Linear contracts are very common on the multitasking literature, but they are not fully optimal in general.[8] The main reason behind the extensive analysis of this type of contracts is that they are widely use by firms.[9] At some extent, it can be explained by their simple structure, but as Bose, Pal and Sappington [6] show in a broad class of environments, "a principal can always secure with a linear contract at least 95% profit that she secures with an optimal unrestricted contract, provided the productivity of the agent's effort is not too meager".[10] In this setting, the parameters of interest to estimate are the marginal contributions of workers actions on the performance measures and the distribution of the marginal cost. To fully back up those parameters, I develop a simple and new methodology to estimate the level of misalignment between performance measures. Perfectly aligned measures should have a constant proportional relationship independently of the contract.[11] When this equality is not satisfied, it is possible to infer the level of misalignment among measures.

The estimated profits show that a contract using both performance measures outperforms a contract using only one. The percentage of profit losses is a convex function of the workers' risk aversion parameter given the relative prices of the output and input measures. As the workers' risk aversion increases, the most informative performance measure receives a higher piece rate in detriment of the most aligned performance measure which has always a positive piece rate assigned. When workers' risk aversion is high enough, the firm reduces the risk workers have to bear assigning a positive

[7] Workers do not realize how well they fit with the job requirements until they are in the company. Full monitoring of workers actions by the firm is too expensive. The limited liability and ex-post information asymmetry are sufficient conditions to have a performance threshold as part of the optimal linear contract.

[8] Linear contracts can be fully optimal contracts in some special settings, as those presented on: Shavell [36]; Holmstrom and Milgrom [20]; Innes [23]; Bhattacharyya and Lafontaine [5]; Sung [38]; Kim and Wang [27]; Corbett, DeCroix and Ha [9]; Pfeiffer* and Velthuis [32]; Carroll [8].

[9] Bhattacharyya and Lafontaine [5] observe that "Linear pricing rules have been found in a number of diverse areas such as, but not limited to, sales force compensation, sharecropping, leasing arrangements, author's fees, legal fees, licensing agreements, commercial real estate rental fees, and franchising."

[10] On the same lines, Raju and Srinivasan [34] found that a quota-based sale-force compensation plan (linear contract with performance threshold) secures 99% of the profits with an optimal curvilinear agency-theory-based compensation plan as proposed by Basu et al. [4].

[11] The measure of misalignment we use in this paper is equal to the angle between the vectors of marginal contributions of the workers actions on the two different performance measures. When the angle is zero, both vectors have the same direction. As a consequence, one vector is a linear combination of the other by a constant that is independently of the piece rate values of the contracts.

piece rate to the input measure. However, workers would try to increase their variable payments distributing more food than necessary. When workers' risk aversion is low enough the firm reduces the incentives of the workers to misspend food establishing a negative piece rate. The performance threshold plays an important role determining the inflection point of the workers' risk aversion determining when it is beneficial for the firm to assign a positive or negative piece rate to the input related performance measure. A more lenient quota increases workers' uncertainty ex-ante. Assuming a risk aversion parameter of 0.5, we found that the firm profit loss is between 2.5% and 4% per day among workers subject to the incentives scheme, which implies a loss of 2 to 3.6 man-days per day in sector of 80 workers. However, at this level of workers' risk aversion the optimal linear contract have a negative piece rate assigned to the input measure, and as a consequence, the observed change in the contract is optimal if the firm is constrained to non-negative piece rates.

The paper is organized as follow. In section 3.2, I review the economic literature related with this paper. Section 3.3 explains the background of the case study and Section 3.4 develops the model. Section 3.5 presents a summary of the data, the evolution of the main variables related to the production process, the sample selection used on the estimation and a reduced form analysis of the contractual change. Section 3.6 explains the empirical strategy and the results of the empirical analysis are shown in Section 3.7. Section 3.8 concludes.

3.2 Literature Review

Agency theory literature has explored intensively the implications of non-observability of actions and the characteristics of the performance measures available on incentive design. Hölmstrom [19] emphasized the importance of the noise of the performance measures when agents are risk adverse. He established a negative correlation between the strength of the incentives optimally provided and the level of uncertainty of the performance measure which are at the heart of moral hazard models. However, on the empirical counterpart, the economic literature have not found strong evidence supporting it.[12] The lack of a negative correlation among incentive and uncertainty led economists

[12] Prendergast [33] provided a complete review of the empirical relation between risk and incentives.

to point out potential identification problems. Empirically, omitted variables as the level of delegation (Prendergast [33], DeVaro and Kurtulus [13]) or the recomposition of the workforce after the introduction of a new incentive scheme (Lazear [28]) emerged as potential explanations of the different correlations found. Theoretically, the introduction of incentives in multitasking context unveiled also potential unintended effects affecting this correlation (Holmstrom and Milgrom [21], Baker [2]). Workers over or under perform on some actions respect to the optimal level required by the principal. Holmstrom and Milgrom [21] based their result on the complementarity of workers' actions in their cost function, whereas Baker [2] analyzes the differences of the marginal productivities of the actions between the performance measures and the value function of the firm. Building upon these models Baker [1], Feltham and Xie [15], Datar, Kulp and Lambert [12] characterize the performance measures in terms of their informativeness about workers actions and their alignment with the firm's objective. An optimal contract should use performance measures to satisfy both conditions.

In this paper, I extend Baker [1] multitasking model including workers limited liability and ex-post asymmetric information about workers' types. As in Sappington [35] those conditions allow the existence of a performance threshold on the optimal linear contract. However, Sappington [35] focuses on situations without multitasking concerns and risk neutral agents. Park [31] and Kim [26] show that the principal could achieve a first best contract using a performance threshold activating a lump sum bonus when workers have limited liability but there are no information asymmetries. Oyer [30] obtained similar results as the previous papers under the assumption that the participation constraint was not binding but the limited liability constraint was. Our optimal linear contract have the same structure as in Sappington [35] in a multitasking context. However, the performance threshold has two roles: it is a screening device among workers and it balances the informativeness and alignment of the portfolio of performance measures.

On the empirical side, most of the studies considering multitasking context evaluate agents' performance on different tasks after the introduction of a new incentive scheme. Dumont et al. [14] evaluate Canadian physicians, Johnson, Reiley and Muñoz [25] Chilean bus drivers, Feng Lu [16] nursing homes in the US, Courty and Marschke [10] federal - job training programs in the US, Oyer [29] non-linearities on salesperson and executive compensations. There are also fields experiments considering long term effects - Fryer Jr and Holden [17] in public schools on Texas- and controlling for reputational concerns as Hong et al. [22] on Chinese factories. They found evidence that the introduction of a new incentive scheme may leads workers to over perform in some tasks in detriment of relevant tasks affecting the value of the firm.

Few papers analyze how firms select different contractual structures among workers. Slade [37] shows that low powered incentives contracts are offered to the agents when the output of the tasks are complementary or when uncertainty across tasks is highly correlated. Banerjee [3] makes a structural estimation of a multitasking model. He analyzes the impact of different incentives schemes assigned by a cell phone company to three types of outlets – company shops, dealers and retailers. He argues that the differences on baseline demand explain differences on contracts schemes. However, all the empirical papers mentioned so far focus on the complementarity of workers' actions in their cost function as in Holmstrom and Milgrom [21]. In this paper, we focus on the differences between the marginal contributions of the actions on the true objective function of the firm and the performance measures in the sense of Baker [1]. Moreover, Slade [37] and Banerjee [3] do not consider more than one performance measure neither their characteristics.

Finally, there are some empirical studies analyzing the main characteristics of performance measures used by the firms in real contracts. Gibbs et al. [18] use data on incentive contracts for auto dealership managers developing indicators of informativeness, misalignment and potential manipulation of the performance measures. Their main result establishes that firms use as primary measure the best option available along the three previous dimensions. Also, they realize that firms uses more than one performance measure to balance misalignment, but just 25% of their sample use a second performance measure at all. Similar results are obtained in other studies that do not directly measure informativeness. Ittner and Larcker [24] analyze the factors influencing the choice of performance measures in non-management incentives plans. They found that uncertainty plays an important role on the determination of the performance measure used on workers incentive plan. But, they also found that other factors could be important as the desire of the firm to improve the link between pay and firm performance (a concept strictly related to the alignment of measures). While these studies suggest that informativeness and misalignment have a role on the determination of incentives schemes, they did not help us to understand the importance of a well design portfolio of performance measures.

3.3 Background

In this paper, I analyze the case of a leading egg production plant in Peru using two different incentive schemes on the years 2011 and 2012. Those incentive schemes had fixed payment and a variable payment based on different sets of performance measures. A performance threshold activates the variable payment. I show that the different characteristics of the performance measures used on the contract have an impact on the effectiveness of the incentive provision and on the final results of the firm.

In Peru, the average egg's production per month during these years was around 26 metric tones.[13] The firm I am analyzing in this project covers almost 22% of the national production in these years. It is one of the biggest egg producers in Peru and one of the main eggs' providers to Peruvian supermarkets.

3.3.1 Production Process

The main business of the company is the production and sale of eggs. The firm is divided in seven different sectors. Those sectors are spatially separated and have assigned a specific amount of hens. All the managers of each sector report to the general production manager. However, each sector has its own manager, supervisors and workers who are independent from the members of the other sectors. In these circumstances, I study the functioning of the oldest and the biggest sector of the company. This sector has almost 850,000 hens; it counts on average with 76 workers assigned per day to different production units, 4 supervisors and one manager. In section 2.2 from chapter 2, we show some aerial photographs of the sector under analysis.

The productive process in each sector is organized as follows: The hens are assigned to different sheds, which are long-building facilities as those observed in the section 2.2 from chapter 2. Our sector counts with 41 sheds. Those sheds are divided in different production units, 99 in our case. Each shed can have from 1 up to 4 different production units with most of them having 2. Each production unit has one worker in charge of its hens. The worker has to feed the chickens, takes care of the facilities and collects

[13]Source: Peruvian national institute for statistics (INEI).

the eggs laid by the hens. Those tasks are organized following a fixed schedule which is controlled by the supervisors.[14] The fixed schedule is an important characteristic on our case since it reduces the space for substitutabilities on the workers' effort allocation among different tasks.

The hens in each production unit come from the same chicken batch. The chicken batches are groups of hens that are raising together on a raising sector and have the same age. The hens stay in the raising sector until the 18 or 19 weeks of age. Then, the entire batch is reassigned to a production unit where they stay until they are dismissed when they are too old. When a worker is assigned to a group of hens in a production unit, she deals with this group during its whole life cycle until this group is dismissed. So, we are able to clearly identify matches between workers and hens' batches.

The production environment of the sector I analyze did not suffer any major change and was very stable during the period under analysis. Our production environment is characterized by its organization, infrastructure and input characteristics. We had the opportunity to interview the production manager and he confirmed that there were no important changes on the production environment during the period 2011 and 2012. In particular, we asked him about infrastructure improvements on the sector of analysis,[15] changes on the formula of the hens' food, the reporting mechanisms and human resources practices on the sector. They were experimenting new shed buildings on others sectors but no in the sector under analysis. Also, they were planning to focus on the red hen variety and installing new food dispensers per worker that will allow them to fill their sacks of food by their own. However, those changes did not take place until mid 2013.

3.3.2 Workers' Compensation

The workers receive a payment every 15 days. This compensation has a fixed component and a variable component (or bonus). The fixed component is a given amount of money per each day the workers go to work and it is independent on the performance per worker. The monthly fixed payment is around the \$190 American dollars (S/. 500).[16]

[14]In the appendix $B.1$ from chapter 2, you could find a detailed schedule of a typical workday for these workers.

[15]It includes the sheds, the water installations or the distribution of sacks among workers.

[16]1 PEN = 0.38 USD (June 30, 2012).

On the other hand, the variable component had two different structures in our period of analysis. Before March 2012, the variable component of the wage used two different performance measures to determine its value. The total amount of eggs' boxes (360 eggs per box) collected and the total amount of sacks of food (50kg per sack) distributed among hens per worker. The piece rates related to this two measures were the same and equal to $2.66 (S/. 7.00). The firm also established a performance threshold that activates this variable payment. In other words, if workers' performance is below that threshold they just receive the fixed wage; but if workers' performance is above that threshold they also receive the variable payment. The performance threshold level was compared with the sum of the average values of the two performance measures on each payment window. The firm used indistinctly the average value of these two measures in the final calculation of the wage. [17] The incentives scheme was as follows:[18]

$$W^{I}(Q_1, Q_2) = \begin{cases} l & \text{if } Q_1 + Q_2 \leq q \\ F^{I} + b(Q_1 + Q_2 - q) & \text{if } Q_1 + Q_2 > q \end{cases}$$

where $W(Q_1, Q_2)$ is the worker's wage depending on the average of the performance measures (Q_1, Q_2) in the last 15 days,[19] F is the fixed payment, b is the piece rate and q is the performance threshold. Q_1 is the amount of egg's boxes produced per worker and Q_2 is the amount of sacks of food distributed among hens per worker. When the value of $Q_1 + Q_2$ is above q, the workers receive an amount b for each extra unit and they do not receive any variable payment otherwise.

After March 2012, the variable component of the contract was modified. They eliminated the incentives from the amount of sacks of food distributed among hens. In return, the firm duplicated the value of the amount of egg's boxes collected, keeping constant the piece rate and the performance threshold, as follows:[20]

$$W^{II}(Q_1, Q_2) = \begin{cases} l & \text{if } 2Q_1 \leq q \\ F^{II} + b(2Q_1 - q) & \text{if } 2Q_1 > q \end{cases}$$

[17] When we inquire the firm about this issue, they told us that they use both measures indistinctly because they have very similar values.

[18] The superscript "I" refers to the sample belonging to the period previous to the contractual change.

[19] In practice, it was common that the manager of the sector sometimes picked one day to calculate workers' wage instead of the average every 15 days.

[20] The superscript "II" refers to the sample belonging to the period after to the contractual change.

The modification of the variable component of the wage was a decision made by the board of the company at end of 2011. The decision was made and announced to the managers of each sector in mid February 2012. The new incentive scheme started at the first fortnight of March 2012 and workers received their first payment under this new contract on March 10th of 2012. At the end of 2010, the firm changes its production manager. The new production manager established and promoted the recompilation of the information I was able to analyze in this project. At the beginning of 2011, the firm established new formats to keep track of the main variables involve in the productive process. The firm's representative suggested that the collection of this new information was the main reason behind the contractual change. They realized that workers were distributing an excessive amount of food according to their criteria. As a solution, they decided to eliminate the incentives related to food distribution. I will come back to this point on section 3.5.

3.3.3 Performance measures and Tasks

How the performance measures depend on the workers' tasks? On one side, the amount of sacks of food distributed per worker everyday, Q_2, is an informative signal of the physical effort exerted by workers feeding their hens. The feeding process have the following characteristics: Each production unit has on average 10 000 hens which are organized in a grid of cages with 3 hens per cage. Each worker has to lift the sack of 50 kg of food on her shoulders and walks around the rows of cages distributing the food. The average amount of sacks distributed is 23 per production unit everyday.

Feeding the hens is a physically demanding task and it is related to the amount of sack distributed. However, it is necessary to be more precise about how informative this performance measure is about the workers' effort. First, the workers report the amount of sacks distributed everyday. The report contemplates a basic unit of half sack and a supervisor verifies this amount. I assume that differences on effort for an amount lower than 25 kg is negligible since workers have to lift and transport the sack in any case. Second, workers cannot steal or hide sacks of food. Workers arrive to the main offices of the company and a bus takes them in and out of their sector. Third, workers have to attempt to even up the amount of food distributed among all her hens. It is not perfectly observable by the supervisors or the researcher, but the supervisors can still notice big accumulations of food on the production unit and they follow the amount of hens' casualties. In any case, the feeding effort is more related to the physical action of the transportation of the sacks. The amount of food is a performance measure workers can perfectly control and it is not influenced by the other tasks workers have. But, it is not strictly related to final value of the firm. The value of the firm critically depends on the amount of eggs collected.[21]

On the other side, the amount of egg's boxes collected depends on all the different tasks the workers make and other variables that are uncontrollable by the workers. For instance, the weather, the quality or age of the group of hens assigned to the worker and the spreads of illnesses, among others. Such a way, contracts depending on this performance measure entail more risk to bear for workers since they cannot perfectly control its final value. However, this measure is strictly related to the core of the business of the company. The final value of the firm depends on the amount of eggs collected and on the evolution of its price.

Assumption 1. *The total amount of eggs boxes collected is a noisier measure of workers' effort but is perfectly aligned with the final value of the firm, while the total amount of food distributed is a noiseless measure of workers feeding effort but is not perfectly aligned with the final value of the firm.*

Within this framework, the change of the contract seems to be motivated by a cost reduction argument. Workers exert less feeding effort when their contracts do not depend on the food provided to their hens. As a consequence, the firm may have the possibility to save money on food. The production manager of the company confirmed the latter. Effectively, as I show on Section 3.5, the amount of food distributed by the workers decreased after the contractual change but the amount of eggs produced and the profits of the firm reduced as well. On next section I develop a model that provides us with the structure to understand the observed results.

3.4 The model

A risk neutral principal maximizes profits and has a production technology that uses as inputs the worker's efforts on two different tasks, $\{a_1, a_2\}$.[22] The production function has a linear structure, $V(a, \epsilon) = \sum_{i=1}^{2} f_i a_i + \epsilon$, where ϵ is a normally distributed error with mean zero and variance σ_ϵ^2 and f_i is the marginal productivity of a_i. Workers' efforts are unobservable. However, the principal observes two different measures of performance, $\{Q_1, Q_2\}$. By assumption 1:

[21] As it is usual on the multitasking literature we consider the final value of the firm as the gross profit of the firm, prior to agent's compensation and cost of food.

[22] We consider that the feeding effort is the effort related to the task a_2 and the effort of all the other possible actions are related to the task a_1. It is possible to consider the tasks separately but it would not change the results.

$$\begin{bmatrix} Q_1 \\ Q_2 \end{bmatrix} = \begin{bmatrix} g_{11} & g_{12} \\ 0 & g_{22} \end{bmatrix} \times \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} + \begin{bmatrix} \omega \\ 0 \end{bmatrix}$$

where ω represents the uncontrollable events (risk) - from workers' perspective - on the performance measure Q_1, eggs collected. Those uncontrollable events have zero mean and variance σ_ω^2. On the other hand, workers perfectly control the realization of Q_2, food distributed. I also consider that the production function of the firm is perfectly aligned with the first performance measure, then $V = Q_1$. On the contrary, it is clear that Q_2 is not perfectly aligned with the production function of the firm. Q_2 does not depend on a_1 and the marginal effect of action a_2 on Q_1 and Q_2 might differ. We consider that a performance measure, Q_s, is not aligned with the production function of the firm if the vectors of marginal contributions of the workers' actions on these measures have different directions. In other words, the angle among those vectors is different from zero.

Workers are risk averse and they want to maximize their net utility – workers' utility as a function of wage received, $U(W(a))$, minus their cost to provide effort, $C(a)$. $U(W(a))$ is a mean variance utility function with $E[U(W(Q(a))] = E[W(Q(a))] - (\rho/2)Var[W(Q(a))]$, where ρ is the coefficient of absolute risk aversion. The cost function is $C_j(a) = \frac{c_j}{2}\sum_{i=1}^{2} a_i^2$ for worker j. It is convex and separable on the effort assigned to each task. The effort exerted in one task is independent of the assignment of effort in other activities. This assumption is in line with the fixed schedule workers have on the company. Also, notice that the marginal cost is equal across tasks since they are both physically in nature. c_j is unknown by the principal and the workers before to sign the contract, but its distribution is known. It is an independent and identically distributed random variable over the support $[\underline{c}, \overline{c}]$, where $\overline{c} > \underline{c} \geq 0$.[23] Each worker privately observes her value of c_j after signing the contract.[24] For simplicity, we let the mass of workers being equal to 1. Finally, I also assume that workers have limited liability. It means that the principal has to ensure a minimum level of utility for the workers after they have signed the contract independently of the output produced by the workers. In particular, I focused on the case of "zero-liability" proposed by Sappington [35], where the minimum level of utility the workers can obtain ex-post is equal to her outside option. Moreover, workers outside option have on average a zero value, which reflects a very competitive labor market for low skill workers as in our case.

The timing of the decisions is as follows: 1) The principal offers a contract based on the

[23]We do not impose any constraint on the maximum value of $\overline{c}$, it could be infinite.

[24]In our case of study, for instance, it may capture the level of worker adaptation to the job environment, her physical capabilities or her probability to get injured.

observables performance measures $W(Q)$, where $Q = (Q_1, Q_2)$. 2) The worker accepts or does not accept the contract; 3) Once the contract is accepted, c_j is observed by each worker j but not by the principal; 4) The worker chooses how much effort to exert per task, $a = (a_1, a_2)$ or to leave the company. 5) Finally, the payoffs are realized, $\Pi(a)$ and $W(Q(a))$. So, the problem of the principal is

$$\underset{W(a),a}{Max} \quad \mathbb{E}_c \left[\mathbb{E}\left(p_1 Q_1(a) - W(Q(a)) - p_2 Q_2 | c\right)\right]$$

subject to

$$\begin{aligned}
& a \in \underset{\tilde{a}}{argmax} \quad \mathbb{E}\left(U^a(W(Q(a)) - C(a)|c = c_j\right) \;\; (IC) \;\; \forall\, w \\
& \mathbb{E}_c \left[\mathbb{E}\left(U^a(Q(P(a)) - C(a)|c = c_j\right)\right] \geq 0 \;\; (PC) \\
& \mathbb{E}\left(U^a(W(Q(a)) - C(a)|c = c_j\right) \geq 0 \;\; (LL) \;\; \forall \;\; w \\
& a_i \geq 0 \;\; (NN) \;\; \forall\, i
\end{aligned} \tag{3.1}$$

where p_1 and p_2 are the prices of egg's boxes and sacks of food, respectively. The principal maximizes her profits under an incentive compatibility constraint for the agent (IC), a participation constraint (PC), a limited liability constraint (LL) and a non negativity constraint for the workers' actions (NN). The PC ensures that the workers would accept the contract ex-ante, before to know her marginal cost realization. The IC deals with the potential moral hazard problem arising when a worker pretends she had a bad realization of c_j, which is not observable by the principal, to justify her choice of low effort. The LL can be interpreted as the maximum fine that can be imposed on the agent for failure to put any effort ex-post to sign the contract. Beyond the presence of moral hazard and adverse selection, we will show later that the informational structure of the problem ensures a complete mapping between c_j and the optimal choice of a, so no randomness is involved in the process ex-post.

3.4.1 Optimal Linear Contract

On this section, I focus on the optimal contract among the set of linear contracts. While linear contracts are optimal just in very specific cases, they are commonly use by their simple implementation. Moreover, they ensure at least 95% of the potential profits using the optimal contract (Raju and Srivanasan, 1996; Bose, Pal and Sappington, 2001). Also, I allow for the possibility to establish a performance threshold activating the variable component of the wages. Thus, the principal potentially offers a contract to her workers with the following structure:

$$W(Q_1, Q_2) = \begin{cases} F + (b_1 Q_1 + b_2 Q_2 - \tilde{q}) & \text{if } b_1 Q_1 + b_2 Q_2 \geq \tilde{q} \\ l & \text{otherwise} \end{cases}$$

This contract generalize the contracts in section 3.3.2. First, I consider different pieces rates b_1 and b_2 for each performance measure. Second, $\tilde{q}$ is a monetary performance threshold which allows me to compare the overall performance of the workers in monetary terms against it. Before the change in the incentive scheme, $b_1 = b_2 = b$ and $\tilde{q} = bq$. After the change, $b_1 = 2b$ and $b_2 = 0$ while $\tilde{q} = bq$ takes the same value. Then, I can redefine the monetary performance threshold, $\tilde{q}$ as a threshold on the marginal cost $\tilde{c}$, where $\tilde{c}$ is the level of the quota where $b_1 Q_1(a_1(\tilde{c}), a_2(\tilde{c})) + b_2 Q_2(a_1(\tilde{c}), a_2(\tilde{c})) = \tilde{q}(\tilde{c})$. As we show later, ex-post there is a unique matching between the marginal cost of the workers and the set of actions selected. The performance threshold screens the most productive workers from the less productive ones. If the marginal cost of a worker is too high, the worker is not able to obtain a variable payment. Then, we can rewrite the contract as:

$$W(Q_1, Q_2) = \begin{cases} F + b_1(Q_1(c) + b_2 Q_2(c) - q(\tilde{c})) & \text{if } c \leq \tilde{c} \\ l & \text{otherwise} \end{cases}$$

The main role of the principal is to select the correct weights on the linear combination of performance measures and the performance threshold to maximize her expected profits. It means to provide the appropriate incentive to her workers to exert the optimal level of effort in both tasks.

We solve the problem using the usual procedure. First, notice that with the zero liability assumption, the participation constraint is satisfied by definition. Then, we replace the incentive compatibility constraint by the first order condition of the agent optimization problem:[25]

$$\frac{1}{c_j}(b_1 g_{11}) = a_1 \text{ and } \frac{1}{c_j}(b_1 g_{12} + b_2 g_{22}) = a_2 \;\; \forall \; j \tag{3.2}$$

Notice that there is a complete mapping between c_j and the optimal actions of the workers. Worker's actions are decreasing on the level of their marginal cost. It implies that if the limited liability constraint holds for the worker with the highest marginal cost receiving the variable payment - $\tilde{c}$, this condition would be satisfied for all the workers with $c_j \leq \tilde{c}$. Since the principal

[25] $\mathbb{E}(W(Q(a)|c = c_j) = F + (b_1 g_{11}) a_1 + (b_1 g_{12} + b_2 g_{22}) a_2 - \tilde{q}$ and $Var(W(Q(a))|c = c_j) = b_1^2 \sigma_{\omega_1}^2$.

is a maximizer the limited liability constraint for the agent with $\tilde{c}$ is binding, then:

$$F = \tilde{q} + \frac{\rho}{2} b_1^2 \sigma_\omega^2 - \frac{1}{2\tilde{c}}((b_1 g_{11})^2 + (b_1 g_{12} + b_2 g_{22})^2)$$

It means that all the workers whose realized c_j is lower than $\tilde{c}$ will enjoy some rents.[26] All the workers with an ex-post marginal cost above $\tilde{c}$ would not receive a variable payment and as a consequence would not exert any effort. However, the limited liability constraint forces the principal to ensure a non-negative ex-post utility to her workers. Thus, unproductive workers receive a zero fixed payment, $l = 0$. Replacing the optimal actions and the fixed wage on the principal expected utility, we are able to obtain the optimal pieces rates as a function of $\tilde{c}$ maximizing against b_1 and b_2:

$$b_1^* = \frac{p_1 \tilde{T}_1 S_1}{2\tilde{T}_2 S_1 + \rho} \tag{3.3}$$

$$b_2^* = \left(\frac{p_1 \tilde{T}_1}{2\tilde{T}_2} - b_1^* \right) \frac{g_{12}}{g_{22}} - \frac{p_2 \tilde{T}_1}{2\tilde{T}_2} \tag{3.4}$$

where $\tilde{T}_1 = E\left[\frac{1}{c} | c < \tilde{c}\right]$ is a measure of expected marginal productivity of the workers, $\tilde{T}_2 = \tilde{T}_1 - \frac{1}{2\tilde{c}}$ is part of the expected marginal cost related to the informational rents the principal transfer to the agents and $S_1 = g_{11}^2/\sigma_\omega^2$ is the signal-to-noise ratio comparing the marginal productivity of action a_1 and the noise of the first performance measure, Q_1. Notice the principal can incentivize the workers to exert effort on task a_1 only using Q_1. It explains that S_1 only consider the marginal productivity of this action when she has two performance measures available. The optimal piece rate, b_1^*, is increasing in S_1, $\tilde{T}_1$ and p_1; and decreasing in ρ and $\tilde{T}_2$. On the numerator of b_1, we can relate $2\tilde{T}_2 S_1$ to marginal cost related to the informational rents transferred to the agent and ρ to the risk premium the firm has to pay for the risk workers bear. A higher risk aversion parameter of the workers, ρ, implies a higher risk premium.

To understand the role of the risk aversion of the workers, let us analyze the case where workers are risk neutral. When workers are risk neutral the principal just consider the informational rents on the marginal cost of action a_1. In this case, $b_1^* = (p_1 \tilde{T}_1)/(2\tilde{T}_2)$. Moreover, if there is just one worker type it collapses to $b_1^* = p_1$, which is the optimal value of b_1^* in the first best linear contract.[27] When workers are homogeneous, the principal does not need to offer

[26] In this respect, notice that, if c_j was observable ex-ante, the optimal contract would have a different fixed payment for every worker type, F_j.

[27] To obtain the first best linear contract, we should maximizes $E[p_1 Q_1(a) - C(a) - p_2 Q_2(a)]$ with

any informational rents. As in the case of b_1^*, b_2^* collapse to its optimal in the first best linear contract when workers are risk neutral and they are homogeneous. Also, when workers are just risk neutral, the deviation with respect to the optimal value is the same as in b_1^*. In particular, $b_2^* = (-p_2\tilde{T}_1)/(2\tilde{T}_2)$. The firm loses efficiency when it has to consider the heterogeneity among agents. Notice that the optimal piece rate for input use is strictly negative when worker are risk neutral. A feature we do not observe in any of the contracts offered by the firm.

Returning to the case when risk is important to workers, a higher risk aversion parameter will always reduce the value of b_1^*. It reduces the strength of incentives the workers receive through the amount of eggs produced, Q_1. It would reduce the effort workers exert in both actions, a_1 and a_2. However, the principal can use the second performance measure available, Q_2, to give incentives to exert a level of effort in a_2 closer to its optimal value on the first best linear contract. In such a way, the principal does not reduce so much the strength of the incentives on the second action. However, it generates a misalignment between the amount of effort workers should exert to maximize the production of the firm with respect to amount of effort generated by the contract. Reducing b_1, workers exert less effort on a_1 but they still exert the required level of effort in a_2 by the incentives received through Q_2. The more sensitive workers are to risk, the higher the misalignment the principal is willing to accept to reduce the risk premium she has to pay to the workers. This is at the heart of the trade-off between misalignment and risk when using multiple performance measures.[28]

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respect to a. Remember I am assuming we have homogeneous agents, then $c_j = c \;\forall\; j$. Then, the optimal actions are $a_1 = \frac{p_1 g_{11}}{c}$ and $a_2 = \frac{p_1 g_{12} - p_2 g_{22}}{c}$ if $\frac{p_1}{p_2} \geq \frac{g_{11}}{g_{12}}$. Given equations 3 and 4, b_1^* should be equal to p_1 and $b_2^* = -p_2$ to obtain the optimal allocation of effort in both tasks using linear contracts. In this case, notice that there is no performance threshold.

[28]In our case, the amount of food distributed among hens is a direct input on the production process. As a consequence, the prices of the eggs and the hens' food have also an important role on the determination of the optimal piece rates. In many situations it is not the case. If we normalize the price to an eggs' box to 1 and assume that the price of a sack of food is zero, the optimal piece rates become:

$$b_1^* = \frac{\tilde{T}_1 S_1}{2\tilde{T}_2 S_1 + \rho} \tag{3.5}$$

$$b_2^* = \left(\frac{\tilde{T}_1}{2\tilde{T}_2} - b_1^*\right)\frac{g_{12}}{g_{22}} \tag{3.6}$$

In this case, the same forces I explained before are at play. The principal wants to provide the appropriate incentives controlling by the amount of risk transfer to the workers. Then, the principal balances the level of misalignment against the level of risk her workers bear. However, notice that when workers are risk neutral, $\rho = 0$, or when the second measure is completely misaligned, $g_{12} = 0$, the principal choose a piece rate for the second measure $b_2^* = 0$. Two measures are completely misaligned when those measures depend on totally different tasks. If there are only two tasks, it implies that the angle of the vector of marginal contributions of those actions over the performance measures will be 90 degrees.

3.4.2 Performance Threshold

Up to now, we have considered the optimal determination of the pieces rates given a certain level of the performance threshold. In our case of study, the performance threshold did not change on the two different incentive schemes. However, the same performance threshold will not have the same effect under the two different schemes and it will depend on the amount of risk the principal transfers to the workers. The effect of the performance threshold on the optimal piece rates is related to the distribution of workers types on the market and on the risk aversion parameter of the workers. Remind that the optimal piece rates on previous section depend on $\tilde{c}$ through $\tilde{T}_1$ and $\tilde{T}_2$.

Lemma 1. *The next inequalities hold:*[29]

1. $\frac{\partial \tilde{T}_1}{\partial \tilde{c}} < 0$*, then* $\varepsilon_{\tilde{T}_1,\tilde{c}} < 0$.

2. $\frac{\partial \tilde{T}_1}{\partial \tilde{c}} < \frac{\partial \tilde{T}_2}{\partial \tilde{c}}$*, then* $\varepsilon_{\tilde{T}_1,\tilde{c}} - \varepsilon_{\tilde{T}_2,\tilde{c}} < 0$ *since* $\tilde{T}_1 > \tilde{T}_2$

3. *There is a* c^t *such that:*

   - *If* $\tilde{c} \leq c^t$, $\varepsilon_{\tilde{T}_2,\tilde{c}} \geq 0$.
   - *If* $\tilde{c} > c^t$, $\varepsilon_{\tilde{T}_2,\tilde{c}} < 0$.

A higher $\tilde{T}_1$ will increase production while a higher $\tilde{T}_2$ will raise the principal costs. Then, a reduction on the monetary performance threshold, $\tilde{q}(\tilde{c})$ which allows workers with higher marginal cost to reach the variable payment has the following effects: 1) Reduce the average productivity of the workers, $\tilde{T}_1$; 2) a) It increases the cost related variable, $\tilde{T}_2$ when the value of $\tilde{c}$ is low enough, or b) It decreases the cost related variable, $\tilde{T}_2$ when the value of $\tilde{c}$ is high enough, but not as much as $\tilde{T}_1$. Overall, the reduction on productivity leads the firm's decision. To understand the impact on $\tilde{T}_2$, notice that the reduction the monetary performance threshold implies a higher fixed wage to cover the limited liability constraint of the less productive worker able to obtain a variable payment; it explains the initial positive effect. However, at some point, the loss of efficiency is so high that the total cost related variable starts to decrease as well. The principal begins to reduce the variable payment.

To fully understand the optimal performance threshold on this linear formulation we need first to understand the impact of $\tilde{c}$ on the optimal piece rates. First, I analyze the case where the firm just uses the perfectly aligned but noisy performance measure, Q_1, on the contract. In such

[29] $\varepsilon_{Y,\tilde{c}} = \frac{\partial Y}{\partial \tilde{c}} \frac{\tilde{c}}{Y}$ is the elasticity of the function Y respect to $\tilde{c}$. The proof is on the Appendix C.5.

a case, the optimal piece rate and the profits are:

$$b_1^{Q_1*} = \frac{\tilde{T}_1(p_1(g_{11}^2) + (p_1 g_{12} - p_2 g_{22})g_{12})}{2(\tilde{T}_2(g_{11}^2 + g_{12}^2) + \phi\sigma_{\omega_1}^2)} \tag{3.7}$$

$$\Pi^{Q_1} = F(\tilde{c})\frac{\tilde{T}_1(\tilde{c})}{2}\left[b_1^{Q_1*}(\tilde{c})(p_1(g_{11}^2 + g_{12}^2) - p_2 g_{12} g_{22})\right] \tag{3.8}$$

where $F(\tilde{c})$ is the cumulative distribution function of the marginal cost of the workers evaluated at $\tilde{c}$ and $\phi = \rho/2$. When the firm is constrained to use just the performance measure Q_1, the principal uses this measure to incentivize both workers' actions. As a consequence, the principal take in account the marginal contribution of both actions on the determination of the piece rate of Q_1. But, those marginal contributions are weighted by the prices of the output and input.[30] To determine the optimal value of the performance threshold, $\tilde{c}$, we need to take the derivative of the profits function against it. We know that $\partial F/\partial \tilde{c} > 0$, $\partial \tilde{T}_1/\partial \tilde{c} < 0$ and it is possible to show using lemma 1 that $\partial b_1^{Q_1*}/\partial \tilde{c} < 0$.[31]

Intuitively, we identify on equation 8 that a higher threshold on the marginal cost $(\tilde{c})$ have three effects firm' profits: 1) It increases the probability to find a worker that is able to obtain the variable payment, $F(\tilde{c})$, and then to exert a positive effort. 2) It reduces the workers average productivity, $\tilde{T}_1$ and 3) the principal will have to choose a lower level of piece rate, b_1, reducing the strength of the incentives provided. The response of the principal on $b_1^{Q_1*}$ is explained by two different forces. First, it reduces the average productivity of the workers and increases the informational rents making less attractive for the principal to incentivize the workers. Second, a more lenient performance threshold allows more workers types to be able to obtain the variable payment. However, it increases the risk workers bear ex-ante because the probability to have a wage depending on a noisy performance measure also increases. Then, the principal will have to pay a higher risk premium.[32] To avoid the high risk-premium, the principal reduce the strength of the incentive, reducing the piece rate of this noisy measure. When the principal

[30] While in this case, b_1 can take negative values, we avoid the analysis of this particular case assuming that $p_1 g_{12} > p_2 g_{22}$.

[31] After some calculations, we know:

$$\frac{\partial b_1^{Q_1*}}{\partial \tilde{c}} = \Delta^{Q_1*}\frac{b_1^{Q_1*}}{\tilde{c}}\left[\varepsilon_{\tilde{T}_1,\tilde{c}}\left(1 + \frac{\phi}{\tilde{T}_2 S^{Q_1*}}\right) - \varepsilon_{\tilde{T}_2,\tilde{c}}\right] < 0 \tag{3.9}$$

where $\Delta^{Q_1*} = \frac{2\tilde{T}_2 S^{Q_1*}}{2\tilde{T}_2 S^{Q_1*}+\rho}$ and $S^{Q_1*} = (g_{11}^2 + g_{12}^2)/\sigma_\omega^2$. We know $\partial b_1^{Q_1*}/\partial \tilde{c} < 0$ given lemma 1.

[32] Ex-ante the workers do not know their types. If the principal increments the domain of workers types having the opportunity to obtain the variable payment, they would have to exert effort in more states of the world being subject to the noise of the performance measure.

chooses the optimal performance threshold, she will prefer a more strict level because it would increase the average workers' productivity, it would reduce the fixed wage payment and it would also reduce the risk premium allowing the principal to increment the strength of the incentives. However, it reduces the amount of workers subject to this incentive scheme since the probability to find high productive workers decreases. It prevents the principal to collapse in an infinite monetary performance threshold or a threshold of value zero on the workers' marginal cost. On the other hand, the firm may choose not to have a performance threshold at all. It will depend on the distribution of the marginal cost. To obtain the optimal threshold, we take logarithms to equation 8 and maximize respect to $\tilde{c}$. We obtain as a first order condition:

$$\varepsilon_{\tilde{T}_1,\tilde{c}} + \varepsilon_{F(\tilde{c}),\tilde{c}} + \varepsilon_{b_1^{Q_1*},\tilde{c}} = 0 \tag{3.10}$$

While we are not able to obtain a closed form solution, our simulations show that for our estimated parameters in our case of study, the performance threshold exists. Moreover, when workers' risk aversion increases, the firm chooses a stricter performance threshold and reduces the strength of the incentive. However, when agents are risk adverse, the principal should consider the noiseless but not perfectly aligned performance measure as alternative. Thus, returning to the case where the principal uses both performance measures, the expected profit of the principal becomes:

$$\Pi_{\rho>0}^{Q_1Q_2} = F(\tilde{c})\frac{\tilde{T}_1(\tilde{c})}{2}\left[b_1^{Q_1Q_2*}(p_1g_{11}^2 + (p_1g_{12} - p_2g_{22})g_{12}) + b_2^{Q_1Q_2*}(\tilde{c})(p_1g_{12} - p_2g_{22})g_{22}\right] \tag{3.11}$$

where the optimal piece rates, $b_1^{Q_1Q_2*}$ and $b_2^{Q_1Q_2*}$, are characterized by equations 5 and 6.[33] Once again, we obtained that $\partial b_1^{Q_1Q_2*}/\partial\tilde{c} < 0$. However, it decreases more than $b_1^{Q_1*}$ because $b_1^{Q_1Q_2*}$ just depend on the marginal productivity of the action a_1 on Q_1. Remember, action a_1 just affects the noisy performance measure while a_2 affects both measures. The principal targets the optimal action a_1 using Q_1 and tune a_2 using Q_2. On the other hand, $\partial b_2^{Q_1Q_2*}/\partial\tilde{c}$ may be

[33]Taking derivative of both optimal piece rates respect to $\tilde{c}$, we obtain:

$$\frac{\partial b_1^{Q_1Q_2*}}{\partial\tilde{c}} = \Delta^{Q_1Q_2*}\frac{b_1^{Q_1Q_2*}}{\tilde{c}}\left[\varepsilon_{\tilde{T}_1,\tilde{c}}\left(1 + \frac{\phi}{\tilde{T}_2S^{Q_1Q_2*}}\right) - \varepsilon_{\tilde{T}_2,\tilde{c}}\right]$$

$$\frac{\partial b_2^{Q_1Q_2*}}{\partial\tilde{c}} = \frac{g_{12}}{g_{22}}\left[\frac{\tilde{T}_1}{2\tilde{T}_2}\frac{p_1}{\tilde{c}}(\varepsilon_{\tilde{T}_1,\tilde{c}} - \varepsilon_{\tilde{T}_2,\tilde{c}}) - \frac{\partial b_1^{Q_1Q_2*}}{\partial\tilde{c}}\right] - \frac{\tilde{T}_1}{2\tilde{T}_2}\frac{p_2}{\tilde{c}}(\varepsilon_{\tilde{T}_1,\tilde{c}} - \varepsilon_{\tilde{T}_2,\tilde{c}})$$

where $\Delta^{Q_1Q_2*} = \frac{2\tilde{T}_2S^{Q_1Q_2*}}{2\tilde{T}_2S^{Q_1Q_2*}+\rho}$, $\phi = \rho/2$ and $S^{Q_1Q_2*} = (g_{11}^2)/\sigma_\omega^2$.

positive or negative. When the threshold on the marginal cost is small enough, it implies that an increase in $\tilde{c}$ will increase $b_2^{Q_1Q_2*}$ because it helps to deal with the amount of risk premium assigned to the workers. However, when the threshold on the marginal cost is high enough, the opposite happens because it starts to reduce the average marginal productivity of the workers too much.

Moreover, $\partial^2 b_1^{Q_1Q_2*}/\partial\tilde{c}\partial\rho < 0$ and $\partial^2 b_2^{Q_1Q_2*}/\partial\tilde{c}\partial\rho > 0$. The risk aversion parameter amplifies the effects we mentioned before. When the risk aversion parameter increases, the principal will have to reduce the strength of the incentives on the action a_1, but she still can incentivize the workers to exert the optimal level of action a_2 increasing b_2. This also affects the selection of the optimal level of the threshold on the marginal cost, $\tilde{c}$. There is a relationship between the use of the second performance measure and optimal performance threshold. Maximizing 3.11 respect to $\tilde{c}$ and equalizing to zero we obtain:

$$\varepsilon_{\tilde{T}_1,\tilde{c}} + \varepsilon_{F(\tilde{c}),\tilde{c}} + \varepsilon_{b^{c*},\tilde{c}} = 0 \tag{3.12}$$

where $b^{c*} = mc_{a_1} b_1^{Q_1Q_2*} + mc_{a_2} b_2^{Q_1Q_2*}$ is a compound piece rate, $mc_{a_1} = (p_1 g_{11}^2 + (p_1 g_{12} - p_2 g_{22}) g_{12})$ and $mc_{a_2} = (p_1 g_{12} - p_2 g_{22}) g_{22}$ are the marginal contributions of the actions controlling by the prices of eggs and hens' food. The main difference between equations 3.10 and 3.12 is on this third component of each expression. While in equation 3.10 just captures the effect of $\tilde{c}$ on the piece rate assigned to the noisy performance measure, on equation 3.12 it is a weighted effect over the portfolio of performance measures. The three tools the principal has available will interact with each other in order to determine the final contract specification. Once again, I cannot establish a closed form solution, but we can analyze some of the mechanisms at play. In particular, if $\varepsilon_{b^{c*},\tilde{c}} > 0$ or $\varepsilon_{b^{Q_1*},\tilde{c}} < \varepsilon_{b^{c*},\tilde{c}} < 0$, the pressure to reduce the performance threshold will be lower than in the case using just the perfectly aligned but noisy performance measure. On the simulation, we found that the use of both performance measures allows the principal to have a more stable performance threshold level when the risk aversion parameter increases. When the workers are more sensitive to the risk, the principal reacts increasing the optimal piece rate of the less aligned but noiseless performance measure, b_2. It allows the principal to choose a more lenient performance threshold. Increasing the weight of the amount of food distributed on the final contract, the principal avoids reducing too much the strength of the incentive and the domain of worker types subject to this incentive scheme.

3.5 Data analysis

The firm provided me with detailed daily information on eggs collected and food distributed by worker and production unit. Alike, we had access to the workers' payment sheets and their employment assistance per day. The information covers a period from January 2011 to July 2013. The daily production reports contain information about the total amount of eggs produced and its classification by quality.[34]. It also has information of the amount of sacks of food distributed, the number of hens assigned to each production unit per day and at the beginning of its production cycle, the number of hens' casualties per day and the age of the hens. This information allows me to identify the periods of hens' replacement and the different size of the production units. Table 3.1 presents a summary of the main statistics obtained in those production reports. Each production unit have on average around 10 000 hens. The age of the hens varies from the minimum of 18 weeks to the maximum of 87 weeks.[35] The average amount of food distributed is 23 sacks of food per production unit or 114.5 grams of food per hen. The amount of eggs' boxes produced is 22, very close to the amount of sacks distributed. It is the main reason why the firm duplicates the value of the first performance measure in the second contract.

Figure 3.1 shows the evolution of the amount of food distributed per hen by the workers from 2011 to mid 2013. The black dotted vertical lines indicate the steady state periods we consider on our empirical analysis. Those stable periods are characterized by the stability of the feeding effort of the workers.[36] The red vertical line represents the day when the contractual change took place. The purple dots show the amount of production units affected by the EDS at the end of 2012.[37] It is possible to identify the reaction of the workers under these changes that were taking place in the company during the period of analysis. First, notice the growing pattern observed during 2011 that triggers the contractual change decision. The reduction on the average amount of food per hen starts on the second fortnight of November and it declines even further in February and March 2012. Those reductions coincide with the dates the firm provides us. The lowest value on the amount of food is on the period after the workers received their first payment and it coincides with the highest levels on the standard deviation on the amount of food distributed as shown on Figure 3.2. On Figure 3.2, we can also observe high volatility at the beginning of 2011 when the new data formats were introduced and at the end of 2012 when the EDS affects several production units.

[34] The classification assigns them into good, dirty, porous or broken categories.

[35] Most of the hens start laying eggs on week 20.

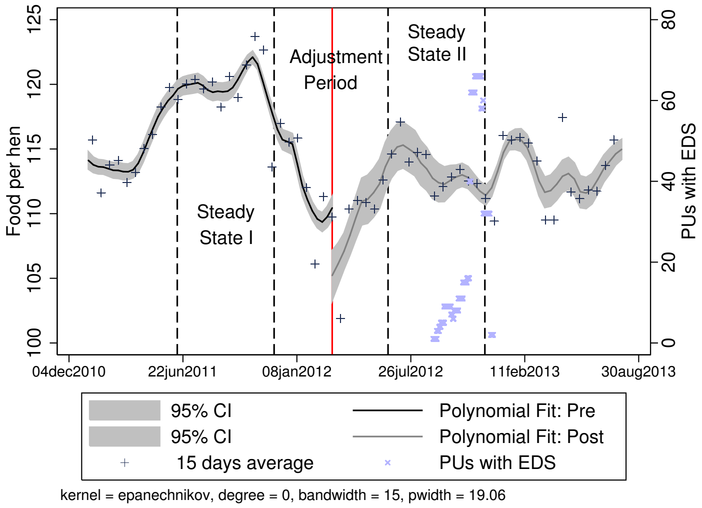
[36] The first period is from June 12th, 2011 to November 29th, 2011 and the second one is from June 16th, 2012 to December 3rd, 2012. More details in the next subsection.

[37] EDS - Eggs Drop Syndrome. It is an illness that affects the amount of eggs laid by the hens.

Variables	**No. Obs**	**Mean**	**St. Dev.**	**P25**	**P50**	**P75**	**Min.**	**Max.**
No. of Hens	78633	10025	3775	7281	11040	13109	2.00	15985
Hens' age (weeks)	78633	46.24	17.14	31.00	46.00	60.00	18.00	87.00
Hens' casualties per day	78171	2.50	2.56	1.00	2.00	4.00	0.00	104.04
Food (50kg sacks)	78633	23.01	8.97	16.50	25.00	30.00	0.00	39.00
Food per hen (grams)	78633	114.42	37.61	113.40	117.26	120.03	0.00	6057.27
No. of eggs	78633	7984	3691	5090	8880	11040	0.00	15131
Egg's boxes	78633	22.18	10.25	14.14	24.67	30.67	0.00	42.03
Eggs per hen	78633	0.79	0.21	0.79	0.85	0.90	0.00	1.00
Good/Total	78631	0.69	0.20	0.64	0.75	0.82	0.00	0.94
Broken/Total	78011	0.02	0.03	0.01	0.01	0.02	0.00	1.00
Porous/Total	78018	0.05	0.06	0.02	0.03	0.07	0.00	1.00
Dirty/Total	78018	0.06	0.04	0.03	0.05	0.07	0.00	1.00

Notes. The table reports the summary statistics of the main variables on the production report. On this table, I consider all our observations from January 2011 to July 2013.

Table 3.1: Summary Statistics

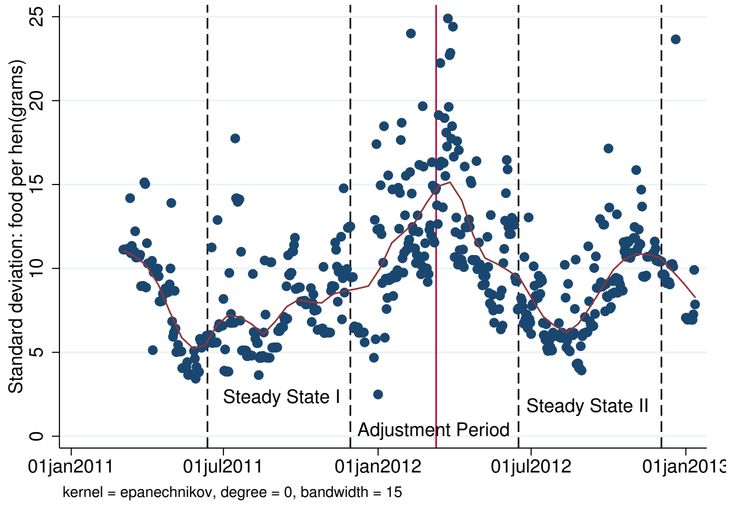


Notes. This graph plots the kernel-weighted local polynomial approximation to the food per hen in grams by production unit from January 2011 to July 2013. The graph shows the smoothed average together with its 95% confidence interval. The black dotted vertical lines depict two steady state periods. The red vertical line depicts the day the contractual change took place. The crosses marks depict the average every 15 days. We use all the sample.

Figure 3.1: Food per hen: Mean

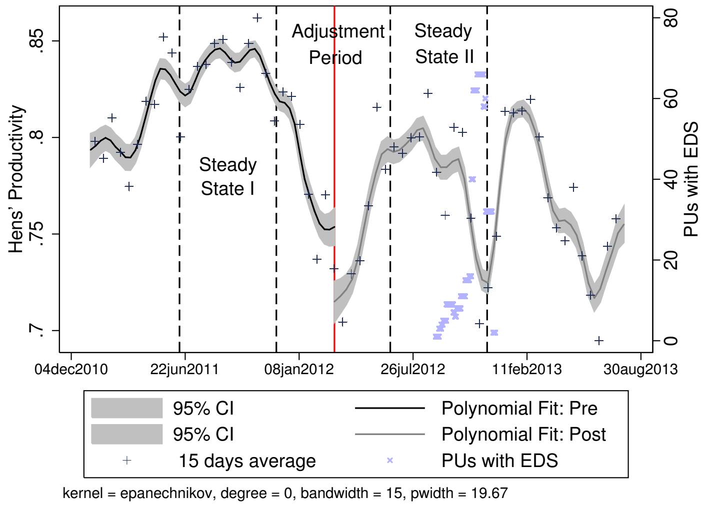
Figure 3.3 shows a similar pattern for the hens' productivity. However, the impact of the EDS is stronger on this variable.[38] Figure 3.4 shows a positive relationship between the amount of food distributed and the amount of egg's produced. The polynomials fit in both figures suggest a monotonically increasing relationship with flat sections at the tails and a stepper section on the middle values. The flat section on the highest values of these variables opens the possibility to reduce part of the feeding cost without affecting the total production. The main objective of the firm was to reduce total cost pay by the food without reducing the egg's production level.

[38]There are also similar patterns on the amount of good eggs over the total number of eggs' produced by production unit. However, the number of hens' casualties is not affected by the contractual change as you cans see on the Appendix C.1.



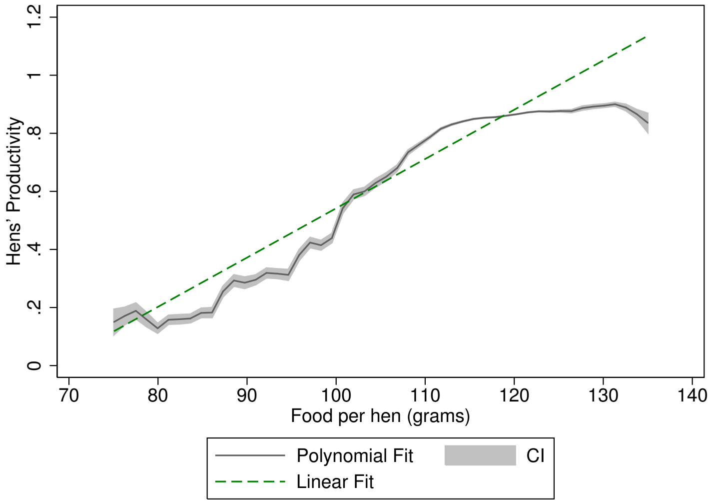
Notes. This scatter plot depicts the standard deviation of the food per hen per day across production units. The red line is the kernel-weighted local polynomial approximation to this variable from January 2011 to July 2013. The black dotted vertical lines depict two steady state periods. The red vertical line depicts the day the contractual change took place. We use the entire sample.

Figure 3.2: Food per hen: Standard Deviation



Notes. This graph plots the kernel-weighted local polynomial approximation to the hens' productivity by production unit from January 2011 to July 2013. The graph shows the smoothed average together with its 95% confidence interval. The black dotted vertical lines depict two steady state periods. The red vertical line depicts the day the contractual change took place. The crosses marks depict the average every 15 days. We use the entire sample.

Figure 3.3: Hens' productivity over time



Notes. This graph plots the relation between the hens' productivity and the amount of food per hen distributed per each worker. It also plots the polynomial and linear fit to the data.

Figure 3.4: Hens' productivity and Food per hen

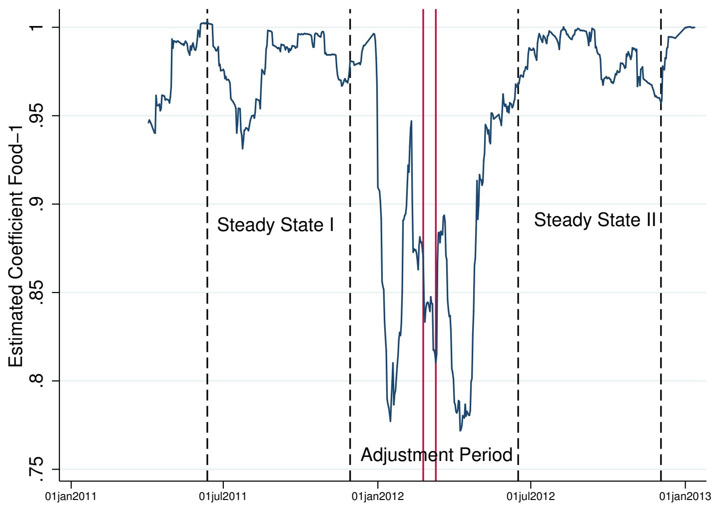
3.5.1 Sample selection

On the estimation exercises, I will focus on a subsample that allows me to deal with different identification issues found in the empirical moral hazard and multitasking literature. In particular, I address the concerns about dynamics and workforce recomposition effects.

Steady States: The model we present in the previous section characterizes the optimal linear contract and workers' behavior in steady state. Fortunately, it is possible to identify two highly stable periods on our sample, one for each type of contract, defined by the covariance of the amount of food distributed per worker in period t and $t-1$. Given assumption 1, the amount of food distributed per worker is strictly related to the feeding effort of the workers. I interpret this covariance as a measure of how persistent observed workers' action is. As our main interest is on the evolution of this covariance over time, I run a regression with a 30 days window that is moving over our whole sample. Then, I assign the estimated β coefficient to the last day in the subsample under analysis. The regression specification is the following:

$$food_{it} = \beta \times food_{it-1} + \alpha_1 \times age_{it} + \alpha_2 \times age_{it}^2 + \phi_i + \psi_t + \varepsilon_{it} \tag{3.13}$$

where $food_{it}$ is the amount of sacks of food distributed per worker i on day t. age_{it} is the age of the hens in weeks, ϕ_i are workers fixed effects and ψ_t are day fixed effects. The age

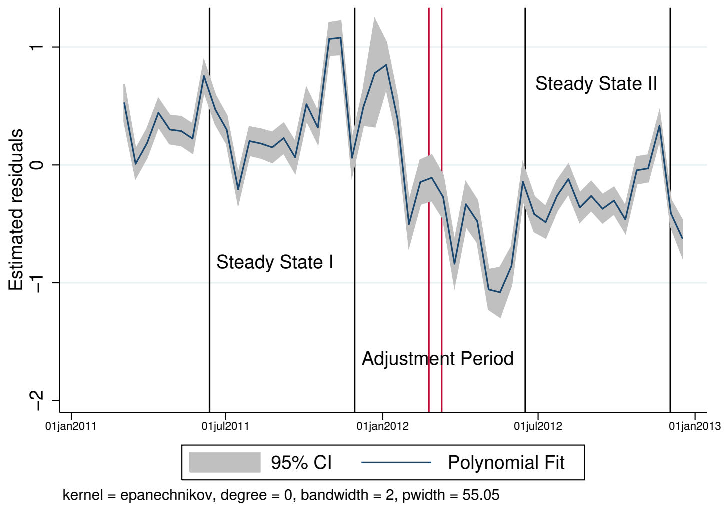


Notes. The figure plots estimated coefficient of $food_{it-1}$ from the rolling regression specified in equation 3.13 with a 30 days window. The vertical red lines indicate the first fortnight after the change in the incentive scheme. The vertical black dashed lines determine our selected steady state periods. The first period is from June 12th, 2011 to November 29th, 2011 and the second one is from June 16th, 2012 to December 3rd, 2012.

Figure 3.5: Steady States: Rolling regression

variables helps us to capture the concave pattern relation between the amount of food and the age of the hens presented in Figure 2.4 on chapter 2. We do not include any other variables potentially correlated with the lagged value of the amount of food as the number of hens. Figure 3.5 plots the estimated coefficients of the lagged value of the food variable. On the figure, we can identify that the covariance among workers' action today and tomorrow decreases on the same period where the decision to change the contract was taken and executed. On the plot, there are two regions, before an after the change, were the strategies of the agents were relatively stable form one day to the other. There is also a disruptive event coinciding with the contractual change that force the agents to adapt towards a new stable strategy. Thus, I define two time periods with the same window of 170 days pre and post change in the contractual structure. The first period is from June 12th, 2011 to November 29th, 2011 and the second one is from June 16th, 2012 to December 3rd, 2012.

Figure 3.6 provide more evidence on the actions stability on the periods selected. It plots the estimated residuals that we obtain after we regress the amount of sacks of food per day against other variables as number of hens, hen's age and age square of the hens, worker fixed effects, shed fixed effects, characteristics of the day as temperature, humidity or production units affected by EDS.[39] We isolate the variability generated by the contractual change on the action of the workers. The pattern obtained points out in the same direction as the previous figure. The residuals before the contractual change are most of the time above zero while the residuals after the contractual change are below zero. Once again, this series reaches it lowest value after the workers receive their first payment and then it increases up to a new more stable level.



Notes. The figure plots the estimated residuals that we obtain after we regress the amount of sacks of food per day against number of hens, hen's age and age square, worker fixed effects, sheds fixed effects, day characteristics and number of production units with EDS. The vertical red lines indicate the first fortnight after the change in the incentive scheme. The vertical black dashed lines determine our selected steady state periods. The first period is from June 12th, 2011 to November 29th, 2011 and the second one is from June 16th, 2012 to December 3rd, 2012.

Figure 3.6: Steady States: Estimated Residuals

Workforce Recomposition: The effect of a contractual change may be explained by a change on workers' behavior or by a change on the composition of the workforce. Lazear [28] showed that incentive effects and selection effects were equally important on the productivity gains in a company after the introduction of a piece rate scheme. If the effects of the contractual change are due to a workforce recomposition effect, it implies that some characteristics of the workers involve in the production process will be more predominant than before. For instance, more able CEOs gravitate to firms offering higher variable payments as a function of the firm performance. However, this paper wants to capture the incentive effect. Thus, I focus on the same set of

[39]The Egg Drop Syndrome (EDS) is an illness reducing the amount of egg's dropped by the hens and theirs quality. It affects some production units on this sector on November and December 2012.

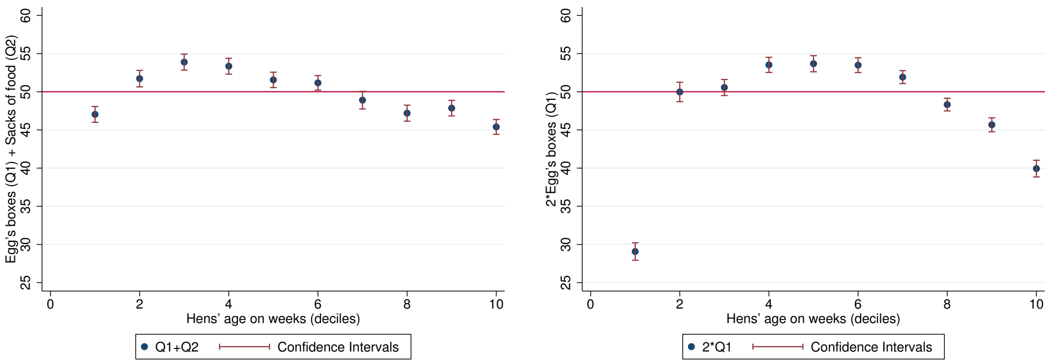
workers on the steady states defined before and after the contractual change. Those workers represent 47% of the whole sample but they account for 85% of the workers per day on our subsample. Using this subsample, workers characteristics variations are minimized. The main objective is to capture only the change in actions due to the exposure of the workers to the new contractual structure.

Performance threshold: The value of the performance threshold established by the firm remained the same before and after the incentive scheme change. [40] The performance threshold plays an important role on the determination of the optimal linear contract as shown in section 3.4.2. It rules out some workers from getting the variable payment. The reason could be because they are unproductive or inputs' quality they have assigned is too low. In particular, hens with different ages have different productivities, which impact the workers probability to reach the performance threshold. Figure 3.7 divides the hen's age in deciles and plots the average value of the performance measures among workers. The red line depicts the performance threshold established by the firm. In both cases, the first and last deciles - the youngest and oldest hens - are the hens with performance measures further away from the performance threshold.

Moreover, Figure 3.8 shows the standard deviation on hens' productivity by hen's age. The red vertical lines identify the limits of the first and tenth deciles of hen's age. As you can notice, those groups have the higher standard deviation on the whole sample. The performance threshold selected by the firm makes more difficult for workers with the less productive and more volatile hens to obtain a variable payment. However, a comparison between the agents' behavior pre and post the contractual change suggest that the workers were using the amount of food distributed to reach the performance threshold in the first period. Since the objective to estimation exercise is to recover the main parameters of the production environment I will focus on the subset of hens with ages between 25 weeks and 70 weeks of age. Hens on this subset have more stable production levels. Thus, production levels depends more on workers productivity.[41]

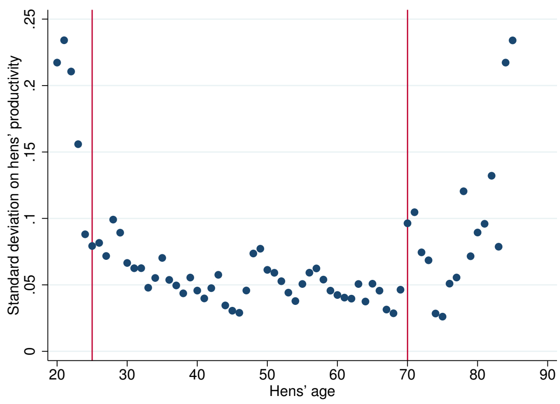
[40] Before the change, they compare the sum of the two performance measure ($Q_1 + Q_2$) against 50. After the change, they compare twice the first performance measure ($2Q_1$) against the same number.

[41] I had also discarded the information for some days in our sample. The main reason was the inaccuracy in the data. Those days coincide with the main holidays of the country - Christmas, New Year and Independence Day and with a recodification on the shed codes used by the workers and supervisors on the sector in May 2012. We eliminate 17 days in total. We were able to identify the data misreporting using the starting number of hens daily reported, the hens' breed and the worker assigned to each of the production units over time.



Notes. These graphs compare the average performance of the workers per hens' age deciles against the performance threshold established by the firm. The left hand side panel plots the average value among workers per production unit of the amount of eggs' boxes collected plus the amount of sacks of food distributed by deciles of hen's age. It considers the information for the first steady state period (pre contractual change). The right hand side panel plots the average value per worker of twice the amount of egg's boxes produced by deciles of hen's age. It considers the information for the second steady state period (post contractual change). The horizontal red line is the value of the performance threshold established by the firm. It was the same in both periods. The workers receive a variable payment when they obtained a performance above that level. We also include their confidence intervals. We consider the subset of workers present on both steady states.

Figure 3.7: Performance measures versus performance threshold: Pre and post contractual change



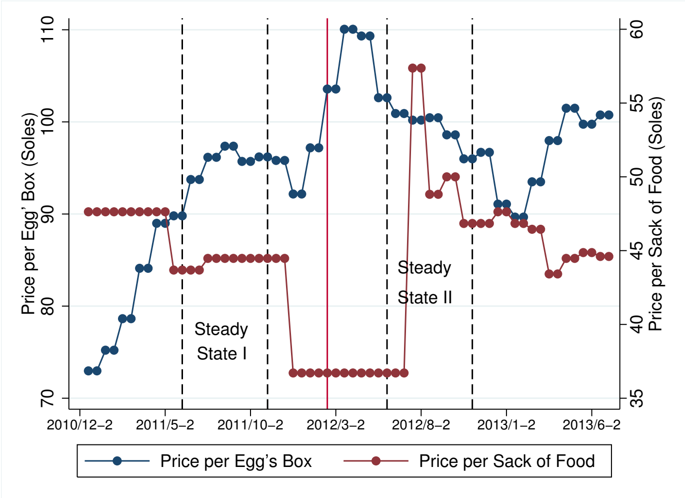
Notes. This figure plots the standard deviation of the hens' productivity by age. We use the information belonging to the steady states periods.

Figure 3.8: Standard deviation on hens' productivity by age

3.5.2 Profits, prices and wages

The workers' payment sheets allow me to match the production units with the workers and give me information about the fortnight payments they received. Table 3.2 provides a summary of the fixed and variable payments of the workers over the whole period of analysis and in three different subsamples: steady state I, adjustment period and steady state II.[42] First, notice that the fixed payment and the total payment increase when we move from the first steady state to the adjustment period to the second steady state. At the same time, the volatility of those categories takes the highest value in the first steady state and the lowest value on the adjustment period. The result seems odd but the fixed payment is an amount of money per workday. It implies that if a worker just works one week he received the daily fixed payment times the number of days worked. And, if a worker is absent one week, another worker can replace her and receives a double payment for that week. The reasons for worker's absence are varied, justified and unjustified. However, the fixed payment totally depends on the presence of the worker on the company and it is not related with the worker performance in any category. On the other hand, the variable payment or bonus increases in mean and variance when we compare the first steady state and the second one. Also, notice that the lowest mean and variance are on the adjustment period. It implies that the workers had a worse performance on this period beyond the fact to have more stability on their assistance as implied by the volatility of the fixed payment. In summary, the total wages of the workers increases in all their components after the contractual change. However, while the volatility of the fixed payment decreases, the volatility of the variable payment increases. The statistics of the variable payment supports our hypothesis that the second contractual arrangement forces the workers to bear more risk. More risk related to the realization of total amount of eggs produced, which is a variable that the worker cannot perfectly control. The model predicts that the higher the risk bear by the worker, the highest the risk premium the principal has to pay.

[42] We are using all the workers and hens' age on this table. The currency unit is Peruvian Nuevos Soles (S/.).



Notes. This figure plots the prices of egg's boxes and sacks of food through the period under analysis. The prices are in Peruvian Nuevo Soles. 1 PEN (Peruvian Nuevo Sol) = 0.38 USD (June 30, 2012).

Figure 3.9: Evolution of Prices

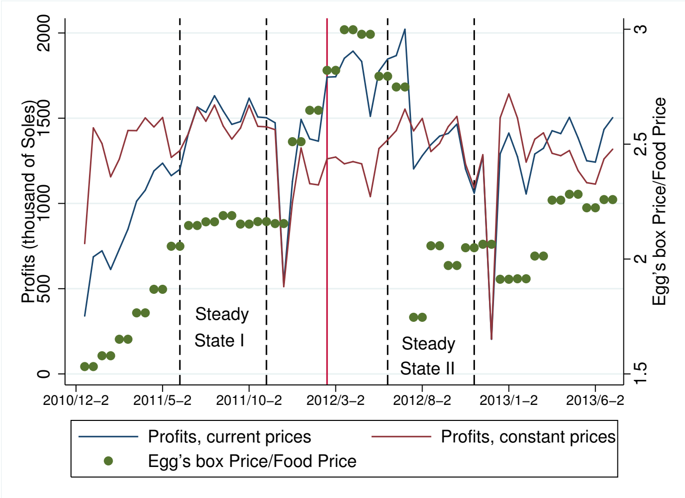
Figure 3.9 shows the evolution of the prices of the egg's boxes and the sacks of food every 15 days during the period under analysis. We observe that the price of the egg's box is constantly changing. We have an average price of egg's box of S/. 95 ($36) in the first steady state period and S/. 100 ($37.8) in the second one. On the other hand, the price of the sack of food presents a more stable pattern per period of time. We have an average price of S/. 44.2 ($16.8) in the first steady state and S/.46.8 ($17.8). On the other hand, the price of food reduces and the price of the eggs' boxes increases just at the same time the contractual change takes place. It is difficult to argue about if there exist or not a casual relationship between the reduction of the production of the firm and the increment on the prices. However, it is clear that if the firm expected it to be the status quo, higher egg's prices and lower food prices the contractual change made no sense. Remember it reduces the food distributed and the amount of egg's produced.

Figure 3.10 plots the profits of the firm and the relative price of the eggs' boxes over the price of the sacks of food. We calculate the average profit per day of the firm using the monthly prices and also using the average price over the whole sample. The blue line depicts the profits of the firm using monthly prices. They follow a very similar pattern as the relative prices scattered on the Figure. The red line depicts the profits using the average prices over the whole sample. Notice that on the steady state both lines overlap almost all the period, except for the first part of the second steady state period. In the next section, I evaluate the impact of the contractual change using a reduced form approximation and controlling for other variables.

Sample	Statistic	Fixed	Variable	Total
Steady	Mean	454.34	84.96	539.82
State I	SD.	144.52	53.30	175.98
	Min	70.50	5.00	35.50
	Max	795.00	289.00	944.00
Adjustment	Mean	490.47	83.59	574.30
Period	SD.	51.65	42.15	68.69
	Min	202.50	15.00	217.50
	Max	560.00	238.00	768.00
Steady	Mean	523.39	87.26	611.33
State II	SD.	61.56	54.90	86.09
	Min	79.50	15.50	95.00
	Max	704.00	386.00	937.50
All Sample	Mean	490.16	85.58	576.26
	SD.	104.21	51.69	128.89
	Min	70.50	5.00	35.50
	Max	795.00	386.00	944.00

Notes. The Table reports the summary statistics of the main payment components of the workers. They are reported on Peruvian currency. Workers are paid every two weeks. 1 PEN (Peruvian Nuevo Sol) = 0.38 USD (June 30, 2012). On this table we use all the workers and hens' age.

Table 3.2: Payment's Statistics



Notes. This figure plots the profits of the firm and the ratio of the output price/input price through the period under analysis. The profits have been calculated using current prices and taking the average prices as constant through the whole period. The profits are in Peruvian Nuevo Soles. 1 PEN (Peruvian Nuevo Sol) = 0.38 USD (June 30, 2012).

Figure 3.10: Evolution of Profits and Ratio of Prices

3.5.3 Impact of the contractual change

The main objective of this section is to answer: Which is the impact of the contractual change on the eggs' collected, food distributed and firm' profits? How does it differ on workers with productive or unproductive hens assigned? I use a reduced form approximation and regress the variables of interest against a dummy taking the value of 1 after the contractual change, the number of hens, the variables related to age, characteristics of the day and worker fixed effects. In this regression we cluster standard errors along both dimensions of day and shed. So, we allow that the idiosyncratic residuals of the regression to be correlated for all observations belonging to the same day and those belonging to the same shed over time. The sample we use consider workers with information in both each steady states. First, we consider all the hens' ages on the sample, but then we divide the sample between productive and unproductive hens.

The results using the whole sample of hens on the period of interest are in Table 3.3. The contractual change has a negative impact of eggs' produced and in the amount of food distributed, but they are significant only on the second variable. The third column has a dependent variable the profits calculated with the average price over the whole sample and columns four and five use the profits calculated with monthly prices. At constant prices, the positive effect of the contractual change is not significant. Using monthly prices, the positive effect is significant

	Egg's Boxes	Sacks of Food	Profits Constant Prices	Profits Current Prices	Profit Current Prices
	(1)	(2)	(3)	(4)	(5)
Contractual Change Dum.	-0.048	-0.871***	31.705	99.032***	27.829
	(0.30)	(0.15)	(23.17)	(28.49)	(45.77)
No of hens	0.002***	0.002***	0.101***	0.105***	0.105***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age	1.081***	0.343***	85.772***	87.743***	87.845***
	(0.08)	(0.02)	(6.22)	(7.55)	(6.61)
Age^2	-0.010***	-0.003***	-0.831***	-0.849***	-0.852***
	(0.00)	(0.00)	(0.06)	(0.07)	(0.06)
Daily Temperature	-0.237*	-0.107**	-16.849	5.511	-15.708
	(0.13)	(0.05)	(11.00)	(13.28)	(10.50)
Daily Humidity	-0.009	-0.016*	-0.007	-0.104	-0.048
	(0.03)	(0.01)	(2.38)	(3.41)	(2.32)
Sheds with EDS	-0.053***	-0.011**	-4.328***	-7.177***	-4.445***
	(0.01)	(0.00)	(0.93)	(1.04)	(0.87)
Price-Egg's Box (S/.)					1435.550***
					(470.25)
Price-Sack of Food (S/.)					-2794.728***
					(400.24)
N	29744	29744	29744	29744	29744
R^2	0.62	0.88	0.43	0.41	0.46

Notes. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Ordinary Least Square estimates. Sample is restricted to the observations belonging to the workers with observations in both steady states periods defined on section 3.5. In this regression, I cluster standard errors along both dimensions of day and shed.

Table 3.3: Contractual change impact on the whole sample

but is no longer significant when we include prices. All the other estimated coefficients are as expected. These results seem to suggest that there was a reduction on food distributed but no real impact on profits since there was an increment on the price of the food. However, this is not the whole picture.

On Table 3.4, I split the sample between hens in unproductive age (columns 1 to 4) and hens in a unproductive age (columns 5 to 8). The contractual change significantly reduced the number of eggs' boxes in 1.5 units (540 eggs) and the sacks of food in 1.1 units (55 Kg) per production unit per day when hens are unproductive. On this subsample, it also generated a significant reduction on profits even after controlling with prices. The reduction on profits was around S/. 390 ($148) per production unit per day. On the other hand, the contractual change generated a significantly reduction on the amount of food distributed among workers with productive hens on the same magnitude than the unproductive ones, 1.05 units (52.5 Kg), but its effect on eggs' produced was no significantly. As a consequence, we obtain a positive and significant effect on profits independently of the value of the prices. The positive impact is around S/.50 ($19) per production unit per day. Overall, it seems to be no impact on the average profit of the firm per day. However, there was an improvement on the efficiency of the workers subject to the incentive scheme. They reduce the amount of food distributed without affecting the level of production and increasing the profits of the firm. However, the nature of the contract generates that the workers that were not able to reach the performance threshold underperform, they reduced the amount of food in such a way that they affected the amount of eggs produced. In detail, workers with productive hens went from 121 grams distributed per hen to 115 grams on average, while workers with unproductive hens went from 112 grams per hen to 106 grams per hen on average after the contractual change. Then the results are consistent with Figure 3.4.

3.6 Empirical Strategy

To estimate the profits of the firm, I take advantages that I observe two different contracts offered by the firm and the fact that there is a one-to-one relationship between one of the performance measures and one of the workers' action.

3.6.1 Misalignment between performance measures

Suppose we have i different performance measures and j different actions. The performance measures has the following structure $Q_i = \sum_l g_{il} a_l + \omega_i$. From the data, we are able to observe the mean and the variance of the performance measures available before and after the contractual

	Hens' Ages < 25 or > 70			Hens' Ages > 25 and < 70		
	Egg's Boxes	Sack of Food	Profits Current Prices	Egg's Boxes	Sack of Food	Profits Current Prices
	(1)	(2)	(3)	(4)	(5)	(6)
Contractual Change Dum.	-1.562*	-1.108***	-389.420**	-0.200	-1.051***	50.706***
	(0.80)	(0.38)	(153.28)	(0.14)	(0.11)	(15.84)
No of hens	0.002***	0.002***	0.059***	0.002***	0.002***	0.124***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Age	2.766***	0.579***	252.762***	0.102**	0.152***	4.577
	(0.34)	(0.09)	(31.85)	(0.04)	(0.03)	(4.04)
Age^2	-0.027***	-0.005***	-2.449***	-0.002***	-0.002***	-0.093**
	(0.00)	(0.00)	(0.32)	(0.00)	(0.00)	(0.04)
Daily Temperature	-0.891**	-0.410***	-29.845	-0.098**	-0.037	-9.858***
	(0.39)	(0.15)	(32.58)	(0.04)	(0.03)	(3.43)
Daily Humidity	-0.081	-0.036	-4.145	0.005	-0.011	0.701
	(0.08)	(0.02)	(7.02)	(0.01)	(0.01)	(0.91)
Sheds with EDS	-0.029	-0.020	0.732	-0.047***	-0.005*	-4.365***
	(0.02)	(0.02)	(1.96)	(0.01)	(0.00)	(0.69)
Price-Egg's Box (S/.)			3372.705***			1229.118***
			(1222.66)			(107.30)
Price-Sack of Food (S/.)			-35.208			-3186.634***
			(784.65)			(177.61)
N	6327	6327	6327	23417	23417	23417.00
R^2	0.51	0.78	0.43	0.92	0.93	0.83

Notes. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Ordinary Least Square estimates. Sample is restricted to the observations belonging to the workers with observations in both steady states periods defined on section 3.5. In this regression, I cluster standard errors along both dimensions of day and shed.

Table 3.4: Contractual change impact by hens' quality

change. The mean and the variance of the performance measures are:

$$E[Q_i] = \sum_l g_{il} E(a_l)$$

$$Var[Q_i] = \sum_j g_{il}^2 Var(a_l) + \sigma_{\omega_i}^2$$

where, $E(a_l) = (\sum_i b_i g_{il}) E(1/c | c < \tilde{c})$ and $Var(a_1) = (\sum_i b_i g_{il})^2 Var(1/c | c < \tilde{c})$ given the model on section 3.4. Following Baker(2002) definition, when two performance measures are perfectly aligned, the vector of marginal productivities of those performance measures have the same direction in the Cartesian plane. Then, if Q_1 and Q_2 are perfectly aligned measures, their vectors of marginal productivities just differ in their scale, $g_2 = k g_1$ where $g_i = (g_{i1}, ..., g_{il})\ \forall i$.

Proposition 1. *Given a constant k, when we have two performance measures, Q_1, Q_2, and two contracts assigning them a piece rate value, $b^I = (b_1^I, b_2^I)$ and $b^{II} = (b_1^{II}, b_2^{II})$,*[43]

1. *When there are more than two tasks, if measures are perfectly aligned then* $\frac{E[Q_2^{II}]}{E[Q_1^{II}]} = \frac{E[Q_2^I]}{E[Q_1^I]} = k$, *but* $\frac{E[Q_2^{II}]}{E[Q_1^{II}]} = \frac{E[Q_2^I]}{E[Q_1^I]} = k$ *if* $(\sum_j g_{1j})(\sum_j g_{2j}) = (\sum_j g_{1j} g_{2j})^2$.
2. *When we have only two actions,* $\frac{E[Q_2^{II}]}{E[Q_1^{II}]} = \frac{E[Q_2^I]}{E[Q_1^I]} = k$ *if and only if measures are perfectly aligned.*

Also, if both performance measures depend only in one and the same action, we would have equality among ratios. More importantly, if the performance measures are not perfectly aligned, we are able to obtain the level of distortion - the angle among the vector of marginal contributions, θ. Let us define $z_1 = \frac{(\sum_l g_{2l} g_{1l})}{(\sum_l g_{1l}^2)}$, $z_2 = \frac{(\sum_l g_{2l}^2)}{(\sum_l g_{1l}^2)}$ and $z_3 = \frac{(\sum_l g_{2l} g_{1l})}{(\sum_l g_{2l}^2))}$. Then, we rewrite the ratio among expected performance measures as:

$$\frac{E[Q_2]}{E[Q_1]} = \frac{z_1 + R z_2}{R z_1 + 1}$$

where $R = b_2/b_1$. Then we are able to state the following proposition.

Proposition 2. *If we have two different performance measures, Q_1 and Q_2, and we observe their realizations under two different incentives scheme, R^I and R^{II}:footnoteThe proof is on the Appendix C.5.*

[43]The proof is on the Appendix C.5.

$$\theta_{gh} = cos^{-1}\sqrt{z_1 z_3} \tag{3.14}$$

where: $z_1 = \frac{R^I X^{II} - R^{II} X^I}{R^I R^{II}(X^{II} - X^I) + (R^I - R^{II})}$, $z_2 = \frac{(R^I z_1 + 1)X^I - z_1}{R^I}$, $z_3 = \frac{z_1}{z_2}$, $X^{II} = \frac{E(Q_2^{II})}{E(Q_1^{II})}$ *and* $X^I = \frac{E(Q_2^I)}{E(Q_1^I)}$.

In our knowledge there are not previous papers identifying the level of distortion among performance measures. Courty and Marschke [11] proposes a test to identify if a measure is distorted on a situation where the marginal productivities varies on different production environments or projects. However, they use a different notion of distortion. They assume that the performance measure depends only on one action and the value of the firm on two different actions. And, their main objective is to identify if the marginal productivity of the common action affects both measure on the same magnitude. Moreover, they assume that the expected deviation of the distortion among projects is zero. It does not apply to our case because we have positive expected distortion among all hen's ages (projects) and we use a more broadly definition of distortion.

In order to estimate the ratio of the expected values of the performance measures, we run a seemingly unrelated regression. We have four different equations that we estimate jointly. I have two equations for each performance measure, one for each type of observed contract. Each regression has the following structure:

$$Q_{jts} = constant + \delta X_{jts} + \varepsilon_{jts} \tag{3.15}$$

Where Q_{jts} is one of the performance measure by worker j in day t on production unit s. X_{jts} are controls as the number of hens, hens' age and age square, temperature, humidity or the amount of sheds with EDS. ε_{jts} is the error term. Then, we estimate the predicted expected value of the performance measure at the mean values of the controls and we calculate the ratios. To estimate the confidence intervals, the standard error of the ratios and the level of distortion we use a bootstrapping technique with replacement using 1000 observations.

3.6.2 Marginal productivities and marginal cost per worker

To fully estimate the parameters of the model, we use the fact it is possible to infer one of the workers' actions through one of the performance measures. Remember that by assumption one, $V = Q_1$ and $Q_2 = g_{22}a_2$. From Q_2, we obtain the workers' action a_2 and replacing it on Q_1. We have that the total amount of eggs collected by worker j is given by:

$$Q_{1j} = g_{11}a_{1j} + \frac{g_{12}}{g_{22}}Q_{2j} + \omega_1 \tag{3.16}$$

The objective is to estimate g_{12}/g_{22} and g_{11}. Then using the estimated angle between the vectors g_1 and g_2, $\hat{\theta}_{g_1 g_2}$, to recover g_{12} and g_{22}. However, a_{1j} is not observable. From the equation 3.2 we can characterize its value before and after the contractual change. Let b be the actual piece-rate parameter before the incentive scheme change. We know the firm used the following piece-rate parameters: $b_1^I = b_2^I = b$, $b_1^{II} = 2b$ and $b_2^{II} = 0$ where I refers to the period before the change and II to the period after. Then, $a_{1j}^I = (1/c_j)bg_{11}$ and $a_{1j}^{II} = (2/c_j)bg_{11}$ for workers above the performance threshold.[44] Let D_j be a dummy equal to one when the observation belongs to the contract after the incentive scheme change. Substituting a_{1j} into equation (16), we get:

$$Q_{1w} = \frac{1}{c_w}bg_{11}^2 + \frac{1}{c_w}bg_{11}^2 \times D_w + \frac{g_{12}}{g_{22}}Q_{2w} + \omega$$

From this expression, we regress the following specification:

$$y_{jts} = \psi_j + \gamma_j \times D_{jts} + \beta \times food_{jts} + \alpha_1 \times age_{jts} + \alpha_2 \times age_{jts}^2 + \alpha_3 \times daytemp_t \tag{3.17}$$
$$+ \alpha_4 \times dayhum_t + \alpha_5 \times edsnum_t + \varepsilon_{jts} \tag{3.18}$$

Where y_{jts} is a measure of the eggs produced by worker j in day t on production unit l.[45] D_{jts} is dummy taking the value of zero for all the observations on the period pre contractual change and 1 for the observations on the period post contractual change. $food_{jts}$ represents the measure of the second performance measure available, Q_{2j}.[46] The variable age_{jts} is the age in weeks of the hens assigned to worker j. It squared is included as well so to capture the reversed-U relationship between hens's age and productivity. We also include workers fixed effects ψ_j as required by the model. We think in ψ_j as capturing the individual fixed effects and any unobserved element affecting her individual's productivity, $\psi_j = \gamma_j + \mu_j$.[47] We also

[44] Also, $a_{2j}^I = \frac{1}{c_j}b(g_{12} + g_{22})$ and $a_{2j}^{II} = \frac{2}{c_j}bg_{12}$ respectively.

[45] We use the same measure consider by the firm on the final contract, the total amount of egg's boxes produced, where each egg's box contains 360 eggs.

[46] Once again, we use the measure consider by the firm on its contract. The contract signed by the workers and the firm have $food_{jts}$ as the daily number of sacks of food distributed by the worker j in day t on the production unit s. Each sack of food contains 50Kg.

[47] It is true that the worker can not choose in which production unit to work but we do not know if the manager assigns them in some particular way. For instance, as a result of the high physical requirements of this type of job, the principal could assign the youngest workers on the production units containing

include some statistics affecting the performance of the workers every day as day temperature ($daytemp$), day humidity ($dayhum$) or the amount of production units affected by EDS that day ($edsnum$). Remember that we run the previous specification using only observations of workers who are observed both before and after the contractual change, so ψ_j and γ_j are separately identified.

The coefficients of interest are the coefficients per worker of the interaction terms (γ_j) and the coefficient of the variable $food_{jts}$. The estimated coefficients are $\hat{\beta} = g_{12}/g_{22}$ and $\hat{\gamma}_j = (bg_{11}^2/c_j)$. Taking logarithms to the second expression, we get $\ln \hat{\gamma}_j = \ln b + 2 \ln g_{11} - \ln c_j$. Since we know $\hat{\gamma}_j$ and b, we can run the regression:

$$\ln \hat{\gamma}_j - \ln b = \phi + v_j \tag{3.19}$$

and get

$$\hat{c}_j = \exp(-\hat{v}_j) \quad \text{and} \quad \hat{g}_{11} = \exp\left(\frac{\hat{\phi}}{2}\right) \tag{3.20}$$

The estimated marginal cost per workers, $\hat{c}_j$, allows me to infer the marginal cost distribution faced by the firm. However, we are just able to obtain a truncated distribution of the cost function. When we estimate $\hat{\gamma}_w$, the workers with the highest marginal cost obtained a negative coefficient. We are not able to take the logarithms of those values as required on expression 3.19. Since the performance threshold is the same before and after the change in the incentive scheme, I first estimated the optimal pieces rates on the linear contract and the firm's profits taking the truncation point of the estimated distribution, $\hat{c} = max(\hat{c}_w)$, as our estimated $\tilde{c}$. Later, as I explained on the next section, I use a log-normal distribution with certain parameters to address the question of the optimal $\tilde{c}$ and we recalculate the profits functions.

Respect to the marginal productivities of workers' actions on the performance measures, we have the estimated impact of action 1 on the amount of eggs' boxes collected, $\hat{g}_{11}$, and the estimated ratio of the action 2 on the different performance measures, $\hat{\beta} = g_{12}/g_{22}$. To disentangle the impact of action 2 on the different performance measures, I use the estimated misalignment across measures, $\hat{\theta}$. By properties of the tangent of an angle, we know that $tan\theta_{g_1 g_2} = \frac{m_1 - m_2}{1 + m_1 m_2}$ where $m_1 = g_{11}/g_{12}$ and $m_2 = g_{21}/g_{22} = 0$ are the slopes of the vectors g_1 and g_2. Then:

more hens. Those types of unobserved matching rules can influence the estimated workers fixed effects but no the worker fixed effect obtained in the interaction term since this type of sorting was present before and after the change. It is the main reason why we focus on the estimated parameter of the interaction term.

$$\hat{g}_{12} = \frac{\hat{g}_{11}}{tan\hat{\theta}_{g_1 g_2}} \quad \text{and} \quad \hat{g}_{22} = \frac{\hat{g}_{12}}{\hat{\beta}} \tag{3.21}$$

To complete our analysis, I estimate the variance of the first performance measure, σ^2_ω from the estimated residuals $\hat{\varepsilon}_i$ of the regression in equation 3.17.

3.6.3 Induced profit losses

At this point we are able to compare the estimated profits of the firm when they have access to two or one performance measures for different values of the workers' risk aversion parameter, $\phi = \rho/2$. Replacing the optimal piece rates in $\Pi^{Q_1 Q_2}$ and Π^{Q_1} defined in section 3.4.2, we get:

$$\Pi^{Q_1 Q_2} = F(\tilde{c})\frac{\tilde{T}_1(\tilde{c})}{2}\left[\frac{(g^2_{11})^2}{\tilde{T}_2 g^2_{11} + \phi\sigma^2_{\omega_1}} + \frac{g^2_{12}}{\tilde{T}_2}\right]$$

$$\Pi^{Q_1} = F(\tilde{c})\frac{\tilde{T}_1(\tilde{c})}{2}\left[\frac{(g^2_{11} + g^2_{12})^2}{\tilde{T}_2(g^2_{11} + g^2_{12}) + \phi\sigma^2_{\omega_1}}\right]$$

Then, to compare among profits we use the concept of induced non-optimality in percentage levels from Raju and Srinivasan [34]. Since we are not comparing those linear contracts with the optimal curvilinear contract, we called this measure induce profit losses:

$$N_{\hat{c}} = \frac{\Pi^{Q_1 Q_2}_{\hat{c}} - \Pi^{Q_1}_{\hat{c}}}{\Pi^{Q_1 Q_2}_{\hat{c}}} \times 100$$

In our case, the profit losses are induced by disregarding the misaligned but noiseless performance measure, Q_2. First, I estimate $N_{\hat{c}}$ given the estimated threshold on the marginal cost, $\hat{c}$. Second, to understand the role of the performance threshold and its relation with the performance measures available, I run a Monte-Carlo simulation assuming that the marginal cost follows a log-normal distribution, $c_j \sim lnN(\mu, \sigma)$. Under a particular set of parameters, I generate 1 000 random samples of 10 000 observations drawn from the selected distribution of c_j. Using them we are able to identify the average optimal $\tilde{c}^*$ for different values of the workers' risk aversion. Once again, we compute the profits considering two performance measures and one performance measure at their optimal estimated performance threshold, $\tilde{c}^*_2$ and $\tilde{c}^*_1$ respectively. The induced profits losses become:

$$N_{\tilde{c}^*} = \frac{\Pi^{Q_1 Q_2}_{\tilde{c}^*_2} - \Pi^{Q_1}_{\tilde{c}^*_1}}{\Pi^{Q_1 Q_2}_{\tilde{c}^*_2}} \times 100$$

The profits are calculated at the worker-production unit-day level and can be aggregated to the sector level or to other time periods. Beyond the fact the workers receive their payments every 15 days, their payment depends on a daily average.

3.7 Results

3.7.1 Estimated parameters

First, I estimate the level of misalignment among the performance measures available. Remember it is the angle between the vectors of marginal productivities of workers' actions on the performance measures. We use a seemingly unrelated regression to obtain the predicted mean of the performance measures under each contract type. The confidence intervals are constructed using bootstrapping with replacement. I estimate three different specifications: without controls, controlling by the number of hens and including all the controls as in table 3.3 and 3.4.[48] The estimated level of misalignment is consistent across specification and around 8.45. Second, I estimate equation 3.17. The results of all the different specifications are in appendix C.2. In this regression I focus on the workers with productive hens assigned. As shown in table 3.4, it allows me to capture the fundamental parameters of the production process. Once again, those regressions cluster standard errors along both dimensions of day and shed. The specification is similar to the specification in column 1 on table 3.3 plus the introduction of the amount of food distributed and the interaction of worker fixed effect with the contractual change dummy as exogenous variables. The estimated coefficients are on line with our previous results. The variable related to the feeding effort has positive and significant point estimates. Taking the value of the coefficient in column 2 as our baseline specification, we know that distributing one more sack of food (50Kg) increases the number of egg's boxes (360 eggs) collected on 0.414. In other words, an increment of 5 grams of food per hen implies an increment of 150 eggs on average per production unit per day.[49] This results are consistent across specifications.

The other estimated coefficients of interest from equation 3.17 are the interaction terms between the workers fixed effect and the contractual change dummy. On the estimation, I find that around 35 over 63 of the workers have a positive estimated coefficient on the interaction term. A negative value on the interaction term is strictly related to a high marginal cost. It implies that only a subgroup of the workers is productive enough to reach the performance threshold activating the variable payment. Figures $C.3$ and $C.4$, on the appendix C.3, show

[48]The estimated parameters for each specification in appendix C.2.

[49]Assuming that the food is evenly distributed among hens.

Est. Par.	Point Est.	St. Error	P-value	95% Conf. Interval	
$\hat{g}_{11}$	0.266530	0.026701	0.000	0.214197	0.318862
$\hat{g}_{12}$	1.794541	0.206152	0.000	1.390491	2.198592
$\hat{g}_{22}$	4.332871	0.591276	0.000	3.173991	5.491751
$\frac{\hat{g}_{12}}{\hat{g}_{22}}$	0.414169	0.030251	0.000	0.354878	0.473459
θ	8.447966	0.4020032	0.000	7.660055	9.235878
$\hat{\sigma}^2_{\omega_1}$	1.041165	0.0247846	0.000	0.992588	1.089742

Notes. The table shows the estimated structural parameters.Sample is restricted to all workers having observations in the period pre and post change in the incentive scheme. We use the subsample belonging to the steady states periods defined on section 3.5 and we do not consider the observations of the hens on the first and tenth deciles of hens' age.

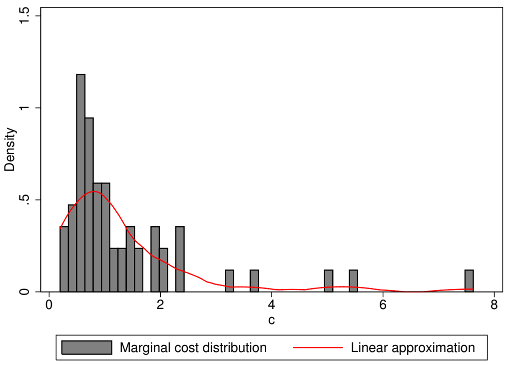
Table 3.5: Estimated parameters

the amount of workers receiving a bonus before and after the change in the contract structure - 30 workers on average. Those estimated coefficients allows me to obtain just a truncated distribution of the marginal cost in equation 3.20. I take its maximum value as a proxy for the performance threshold. Finally, we use the variance of the predicted residuals of equation 3.17 as a proxy for the standard deviation of the worker's uncontrollable effects on the total amount of eggs' boxes produced. The standard errors of the standard deviation have been estimated via bootstrapping (100 repetitions).

Figure 3.11 plots the estimated marginal cost distribution obtained with our basic specification on column 2. The domain of these estimated distributions are approximately between S/. 0 to S/. 10 per unit of effort. The table on Figure 3.11 presents the main statistics of this estimated truncated distribution. We found a positive skewed distribution with a mean greater than the median as expected in an environment with low skill requirements. The marginal cost is reasonable low for most of the workers but not for all. For instance, high marginal cost in this situation can be related to the high requirements of physical workload, the conditions of the work environment or the lack of experience.[50]

All the estimated parameters are on Table 3.5. Notice that feeding effort is really the most important input on the productive process as a whole. It does not only determine the amount of food distributed but also has a higher impact on the amount of eggs collected than the other workers actions. On unit of effort more exerted on a_2 has an impact on the amount of eggs collected that is 6.7 times higher than the impact of one unit of effort more exerted in a_1. Also, the

[50]In the next subsection we will analyze the optimal threshold level using a specific marginal cost distribution in Monte-Carlo simulation.



Moment	Value
$Mean\ c$	1.244983
$Median\ c$	0.583986
$Max\ c$	10.39072
T_1	1.867547
T_2	1.819428
$T_1/2T_2$	0.513224

Figure 3.11: Estimated truncated marginal cost distribution

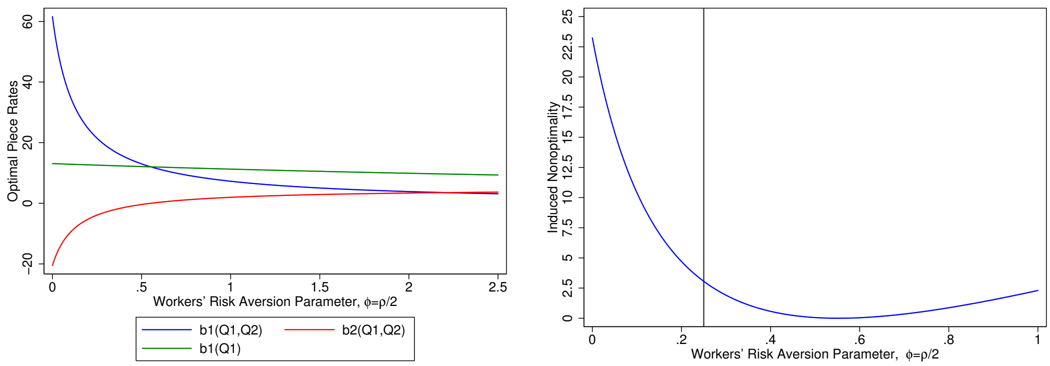
marginal productivity of the feeding effort (a_2) has an impact on the amount of food distributed that more than double its impact on the amount of egg's collected (2.4 times). This result is consistent with our previous findings. The model predicts that the agents subject to the incentive scheme decrease their effort on action a_2 and increase their effort on action a_1, the marginal productivities explain why we observe the reduction on Q_2 while no effect on Q_1 on Table 3.4. Theoretically, the principal uses the the piece rate related to first performance measure (Q_1) to target the optimal level of the effort collecting eggs and she uses the piece rate of the second performance measure (Q_2) to get a better approximation to the optimal level of the feeding effort (a_2). The exact values depend on the worker risk aversion parameter and the prices of the hens' food and eggs.

3.7.2 Estimated Profits

Fix performance threshold

In this section, we calculate and compare the profits of the firm using the two types of incentive scheme observed. First, we obtain the optimal piece rates and $N_{\hat{c}}$ assuming that $\hat{c}$ is the maximum level on the estimated distribution of the marginal cost. I compare the contracts based on one performance measures respect to the contract using both of them for different values of the workers' risk aversion, $\phi = \frac{\rho}{2}$ given p_1 and p_2.

At this point, it is necessary to give more information on the role of the prices. First, in the contract using two performance measures, by inspection of equation 4 it is possible to identify that when $\phi = 0$, b_2^* is negative. At the same, when $\phi \to \infty$, b_2^* is negative if $p_1/p_2 < g_{22}/g_{12}$. Moreover, b_2^* is a continuous function on phi. In our case, this implies that b_2^* should be always negative regardless the value of the worker risk aversion parameter since p_1/p_2 is on average 2.15 and 2.18 in each steady state respectively and $g_{22}/g_{12} \approx 2.41$. On the other hand, we know that b_1^* is always positive. Second, in the contract using just one performance measure, b_1^* is negative is $p_1/p_2 < g_{12}g_{22}/(g_{11}^2 + g_{12}^2)$ independently of the workers' risk aversion parameter. In our case, $g_{12}g_{22}/(g_{11}^2 + g_{12}^2) \approx 2.36$. If we compare the payoffs obtained by these two type of contracts, the results using both performance measures always outperform the contract using just one. However, it implies a negative piece rate on the amount of food distributed. What happen if the manager is constrained and she cannot use negative piece rates? The result suggests that no incentive is a better solution. However, our estimation of prices and profits have to be considered carefully given the set of assumptions we made on their calculation.[51] What happen if we assume a relative prices, $p_1/p_2 = 3$. For instance, $p_1 = 120$ and $p_2 = 40$.



Notes. The left hand side panel plots the predicted piece rates of the optimal linear contract using both performance measures and using just one performance measure. The right hand side panel plots the induced profit losses of the firm when the firm ignores the misaligned but noiseless performance measure on the final contract. The x-axis in both cases is the workers risk aversion parameter, $\phi = \rho/2$. The higher the value of ϕ, the more risk averse the agents.

Figure 3.12: Optimal piece rates and induced profit losses

Figure 3.12 presents the results of the estimated contracts and profits. The left hand side panel plots the optimal piece rates under the two different contracts. On the contract using only one performance measures, b_1^* is positive regardless the worker's risk aversion parameter, but it decreases as the risk aversion increases. When workers are more sensitive to the risk

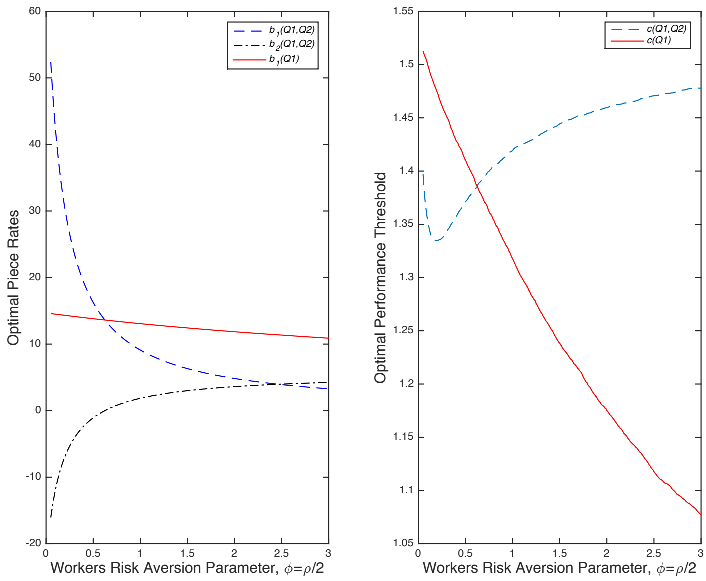
[51] I made several assumptions: 1) The price of the food was indirectly calculated by the firm and in dollars, 2) I use a constant exchange rate, 3) The price is based on the report of the national statistical institute from Peru and the price was per kilogram, 4) I assume that there are on average 15 eggs per kilogram, 5) I made all the required calculations to transform prices in terms of eggs' boxes and sacks of food.

they bear, the principal must reduce the strength of the incentives provided. On the contract using both performance measures, the principal provides stronger incentives on the perfectly aligned performance measure when workers' risk aversion is low and weaker incentives when workers' risk aversion is high. When workers' risk aversion increases, the principal reduces the piece rate of the noisy performance measure and increases the piece rate of the noiseless performance measure. As consequence, b_2^* changes from a negative values given the relative prices to a positive value that generates higher incentive without increasing the risk premium. On the contract using both performance measures, the piece rates can be equal and positive with a very high workers' risk aversion parameter, $\rho \approx 4.5$.[52] A reasonable but conservative value for the workers' risk aversion parameter in our case is $\rho \approx 0.5$ given we have low skill workers in a developing country. It implies, that the firm is moving towards the right direction with the contractual change made. On the right hand side panel, we have the induced profit losses generated when the firm uses only one performance measure instead of both performance measures available. The contracts are exactly the same and therefore profits when workers' risk aversion (ρ) is around 1.08. At the left of this value, the contract using both performance measures have better results because it allow the principal to discourage workers exerting effort on feeding the hens. The principal reduces the cost of food distributed. At the right of this value, the contract using both performance measures have better results because it allow the principal to use both measures to deal with the risk assigned to the workers. In our case, if we assume a value of the risk aversion parameter of $\rho = 0.5$, we obtain that the loss of efficiency for the firm ignoring the more informative but less aligned performance measure was around 2.5% of daily production per worker. Each worker produces 225 eggs less per day, implying a loss around of 2 man-days per day on a sector with 80 workers.

Optimal performance threshold

To extent our analysis and to be able to find the optimal performance threshold, we pursue a simulation analysis assuming a log-normal distribution of the marginal cost among workers, $c \sim lnN(\mu = -0.4, \sigma = 0.8)$. Using this parameterization we randomly draw 1000 distribu-

[52]While we do not know the exact value of the risk aversion parameter in our case of study, we can analyze the values of previous studies. For instance, Rajan and Srivinasan (1997) selects the value of $2/3$ and $3/4$ as their risk aversion measures while Banerjee chooses a value of 0.3. Moreover, we need to consider that those previous studies analyze cases in developed countries while we focus in low skill workers in a developing country. Workers with lower levels of income tend to be more risk averse, especially in developing countries (Gandelman and Hernandez-Murillo 2014). Gandelman and Hernandez-Murillo (2014) estimates the relative risk aversion parameter for several countries. They found that an average relative risk aversion of 0.88 for developed countries and average of 1.01 for developing countries. In particular, they found 1.39 for Peru.

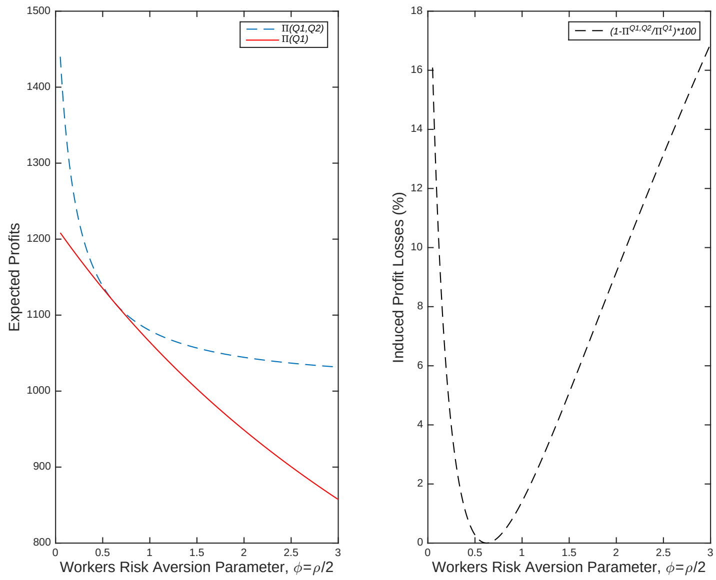


Notes. The left hand side panel plots the predicted piece rates of the optimal linear contract using both performance measures and using just one performance measure. The right hand side panel plots the optimal performance threshold the firm should establish for different values of the workers' risk aversion, $\phi = \rho/2$. The higher the value of ϕ, the more risk averse the agents. To simulate those results, I use a lognormal distribution for the marginal cost of the workers with parameters, $\mu = -0.3095745$ and $sd = 0.9114643$. We replicate 1 000 randomly drawn distributions with 10 000 observations each. Then, we make the corresponding calculations using the model in section 3.4.

Figure 3.13: Optimal performance threshold, $\tilde{c}$

tions with 10000 observations each one. For each drawn distribution, we calculate the expected profits of the firm assuming different values of the risk aversion parameter, $\phi \in [0, 1]$ and the performance threshold, $\tilde{c}^*$. Then, we recover the optimal performance threshold and piece rates that maximize the expected profits of the principal for each value of the risk aversion parameter on the grid. Finally, we take the average value of those variables over the different drawn distributions. Once again, I use the values of the price, $p_1 = 120$ and $p_2 = 40$.

Figure 3.13 plots the optimal pieces rates and the optimal performance threshold obtained on the simulation when the firm considers both performance measures available or just the undistorted but noisy one. The left hand side panel plots the optimal piece rates in each type of contract. They follow the same pattern than those estimated on previous section in Figure 3.12. The right hand side panel plots the optimal performance threshold in each type of contract. The optimal performance threshold monotonically decreases as the level of risk aversion of the work-



Notes. The left hand side panel plots the profits of the firm under the different incentive schemes. The right hand side panel plots the induced profit losses of the firm when the firm ignores the misaligned but noiseless performance measure on the final contract. The x-axis in both cases is the workers risk aversion parameter, $\phi = \rho/2$. The higher the value of ϕ, the more risk averse the agents. To simulate those results, I use a lognormal distribution for the marginal cost of the workers with parameters, $\mu = -0.3095745$ and $sd = 0.9114643$. We replicate 1 000 randomly drawn distributions with 10 000 observations each. Then, we make the corresponding calculations using the model in section 3.4.

Figure 3.14: Simulated Results

ers increases when the principal uses just the undistorted but noisy measure as expected in the model. Remember that a more lenient performance threshold increases the ex-ante risk bore by the workers and then the risk premium the principal has to pay. As a consequence, the higher the risk aversion parameter of the workers, the stricter have to be the performance threshold as response. On the other hand, the optimal performance threshold in a contract using the two different performance measures follows a convex pattern. At the beginning, when the workers' risk aversion is low a similar force as in the one performance measure case predominates. However, when the risk aversion is high enough, the manager can reduce the risk premium assigning a higher weight on the contract on the distorted but noiseless performance measure. It counterweight the other force making the performance even less strict.

Figure 3.14 plots also the expected profits and induced profit losses. The induced profit losses on the right hand panel has the same convex shape as in Figure 3.12. However, when workers' risk aversion is 0.5, we obtain a loss of efficiency for the firm around 3.9% of the daily production per worker. Each worker produces around of one eggs' box less per day. On the contract with just the undistorted but nosy performance measure, the increment on the risk aversion of the workers do not just reduce the optimal quota level but it also reduces the piece rate assigned to this measure. The principal uses both tools to reduce the exposure of the agent to a higher level of risk. It implies a reduction on the strength of the incentives and on the domain of workers types subject to these incentives. When the principal uses both performance measures, she is able to reduce the level of risk bored by the agents assigning more weight to the distorted but noiseless measure. It allows a lower reduction on the strength of the incentives and even an expansion of the domain of worker types subject to those incentives. In both cases, the expected profits of the principal decreases as the workers' risk aversion increment. As expected, it decreases more when the principal have less tools available generating and increasing induce profit losses to disregard the distorted but noiseless performance measure.

3.8 Conclusion

This paper contributes with the literature on performance measures and contract design on multitasking frameworks showing the importance of a well-designed portfolio of performance measures. In a context with risk adverse workers, managers goal is to provide the appropriate incentive minimizing the risk their workers have to bear, to reduce the risk premium. However, an informative performance measure perfectly aligned with the firm preferences is unusual in most productive processes. The absence of a unique performance measure with those characteristics promotes to use a portfolio of performance measures to balance them. However, at the moment, most of the discussion about contracts based on multiple performance measures has been theoretical and the existent empirical literature has focused on the understanding of the characteristics of the performance measure in use. In our knowledge, there are no previous quantifications on how costly could be to focus just on one performance measure having other options available and when it could be beneficial.

We analyze the case of an egg production plant in Peru that change its incentives scheme during our period of analysis. They started with a contract depending on two different performance measures, one perfectly aligned but noisy (total boxes of eggs produced per worker) and another one misaligned by noiseless (sacks of food distributed among chickens per worker). Then, the firm eliminated the misaligned measure from the contract specification and keep just the undistorted but noisy performance measure. This contractual change reduced the amount of food distributed per worker among her hens and has different effects on the amount of eggs produced. For workers with hens in unproductive ages it have a negative impact on the amount of eggs collected but there was no effect on production for workers with hens in productive ages. As a consequence, workers with productive hens increases the profits of the firm but the workers with unproductive hens reduce the profits of the firm. The overall effect on profits was no significant when we control for the output and input prices. However, given the change on those prices, the firm increased its profits.

The optimal linear contract given the estimated parameters for a conservative value of the workers' risk aversion suggests a positive piece rate assigned to the amount of eggs' produced and a negative one for the amount of food distributed. However, in many real situations, negative piece rates are considered a punishment and they are forbidden by legal requirements or by the social conventions among workers. The relative prices of output and input and the workers' risk aversion parameter play an important role when the principal is constrained to non-negative piece rates on the linear contract. As shown in this paper, when the ratio output price/input price is not high enough the firm would rather be better not providing any incentive at all. However, when the ratio output price/input price is high enough the firm would improve efficiency selecting a positive piece rate on the output measure and zero to the input measure. The firm opts for this second approach and they actually increase the efficiency of the workers with productive hens assigned.

Disregarding the nonnegative constraint, we compare the optimal linear contract using both performance measures with the contract using just the output related performance measure. I focus on the case when the ratio of prices makes meaningful to have an incentive scheme. On this situation, the induced profit losses in percentage have a convex pattern as a function of the workers' risk aversion parameter. The minimum level on this convex function is equal to zero in a unique level of the workers' risk aversion $(\phi^m in)$ where both type of contracts generate the same level of expected profits for the firm. For $\phi < \phi^m in$, the contract using both performance measures outperforms the contract using just one measure because the manager can reduced the total cost of food selecting a negative piece rate for the amount of food distributed. For $\phi > \phi^m in$, the contract using both performance measures outperforms the contract using just one measure because the manager can reduce the risk bore by the workers without reducing the strength of the incentive. The firm assigns a positive piece rate to the amount of food distributed while reduces the piece rate of the amount of eggs' collected.

This paper also allows the firm to select an optimal performance threshold activating the variable payment. Unlike previous literature, the performance threshold is not just a screening device among workers characteristics; it also helps the principal to balance the risk workers bear and the level of alignment between the performance measures and the final objective of the firm. The performance threshold determines the domain of workers types subject to the incentive scheme. A more strict performance threshold will reduce the amount of workers types able to activate the variable payment, reducing workers risk ex-ante. As a consequence, when the firm use a contract based just on one performance measure, if workers' risk aversion increases managers will reduce the strength of the incentive and the domain of workers types subject to them. On the other hand, when the firm uses a contract based on both performance measures, the manager can handle an increment on the workers' risk aversion increasing the piece rate related to the amount of food distributed minimizing the reduction on the strength of the incentives and even incrementing the domain of workers' types subject to them.

Assuming a conservative value of the workers' risk aversion parameter ($\rho = 0.5$), I found that the loss of efficiency for the firm would be between 2.5% to 3.9% of daily production per worker if the firm ignores the most informative and misaligned performance measure. As a consequence, each worker would produces between 225 to 360 eggs less per day, implying a loss between 2 and 3.6 man days per day on a sector with 80 workers.

Finally, it is important to highlight that the new and simple empirical analysis I use to identify the level of misalignment among two performance measures could be extended to more general frameworks. It could be important on the development of new portfolio of performance measures either on the design of private contracts or on the requirements for the allocation of resources among public programs.

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Appendix A

APPENDIX: CHAPTER 1

A.1 Mathematical appendix

Proposition 1

Proof. The problem of the manager in a centralized organization depends on the accuracy of the information, p. As a result, the leader faces different probabilities to exchange tasks given the realizations and observability of the state of the world, (t_1^0, t_2^0). The different probabilities are presented in Figure A.1:

In order to calculate the manager's expected cost in a centralized organization and given the linear structure of the utility function - $U(\theta_i, t_i) = |\theta_i - t_i|$ - we have divided the possible realizations (t_1^0, t_2^0) in four subregions of equal size using the established domain of the tasks. The first quadrant, where the probability to exchange task is zero, is $Q1(\theta_1, \theta_2, p)$:

$$
\begin{aligned}
Q1(\theta_1, \theta_2, p) = & \int_{0}^{\theta_1} \int_{0.5}^{\theta_2} (\theta_1 - t_1) + (\theta_2 - t_2) dt_2 dt_1 + \int_{0}^{\theta_1} \int_{\theta_2}^{1} (\theta_1 - t_1) + (t_2 - \theta_2) dt_2 dt_1 \\
& + \int_{\theta_1}^{0.5} \int_{0.5}^{\theta_2} (t_1 - \theta_1) + (\theta_2 - t_2) dt_2 dt_1 + \int_{\theta_1}^{0.5} \int_{\theta_2}^{1} (t_1 - \theta_1) + (t_2 - \theta_2) dt_2 dt_1
\end{aligned}
$$

$$Q1(\theta_1, \theta_2, p) = \frac{1}{8}(3 - 2\theta_1 + 4\theta_1^2 - 6\theta_2 + 4\theta_2^2) \tag{A.1}$$

The second quadrant of the figure A.1 at the top right is represented by the following equation:

$$\begin{aligned}
Q2(\theta_1, \theta_2, p) = &\int_{\theta_2}^{1}\int_{\theta_2}^{1}(p^2 + p(1-p) + (1-p)^2)((t_1 - \theta_1) + (t_2 - \theta_2)) + p(1-p)((t_2 - \theta_1) + (t_1 - \theta_2))dt_2 \\
+ &\int_{1/2}^{\theta_2}\int_{t_1}^{\theta_2}(p^2 + p(1-p) + (1-p)^2)((t_1 - \theta_1) + (\theta_2 - t_2)) + p(1-p)((t_2 - \theta_1) + (\theta_2 - t_1))dt_2 \\
+ &\int_{1/2}^{\theta_2}\int_{\theta_2}^{1}(p^2 + p(1-p) + (1-p)^2)((t_1 - \theta_1) + (t_2 - \theta_2)) + p(1-p)((t_2 - \theta_1) + (\theta_2 - t_1))dt_2 \\
+ &\int_{1/2}^{\theta_2}\int_{1/2}^{t_1}(1-p)((t1 - \theta_1) + (\theta_2 - t2)) + p((t2 - \theta_1) + (\theta_2 - t_1))dt_2 dt_1 \\
+ &\int_{\theta_2}^{1}\int_{1/2}^{\theta_2}(1-p)((t1 - \theta_1) + (\theta_2 - t_2)) + p((t_2 - \theta_1) + (t_1 - \theta_2))dt_2 dt_1
\end{aligned}$$

$$Q2(\theta_1, \theta_2, p) == \frac{1}{24}(p^2(1 - 2\theta_2)^2(-5 + 4\theta_2) - 6(-2 + \theta_1 + (3 - 2\theta_2)\theta_2)) \tag{A.2}$$

The third quadrant expression at the bottom left is as follows:

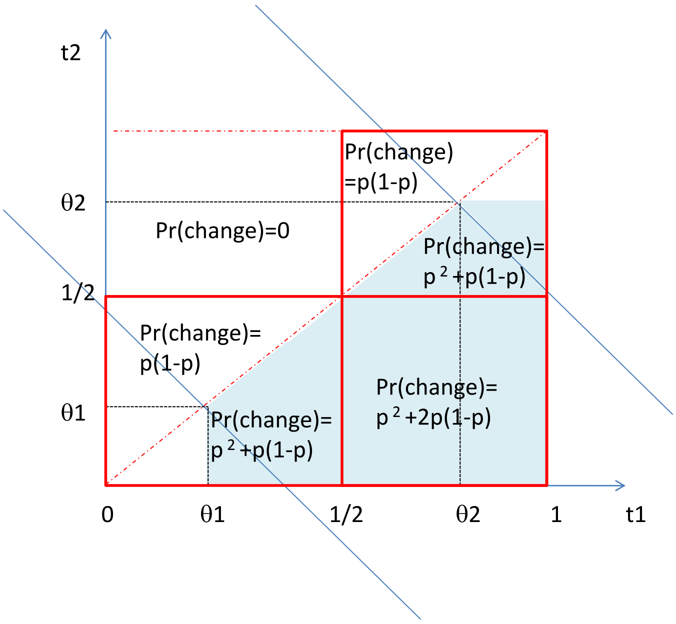


Figure A.1: Probability of Task Reallocation from the Leader's Perspective in a CTR by Region

$$
\begin{aligned}
Q3(\theta_1,\theta_2,p) = &\int_0^{\theta_1}\int_0^{\theta_1}(p^2+p(1-p)+(1-p)^2)((\theta_1-t_1)+(\theta_2-t_2))+p(1-p)((\theta_1-t_2)+(\theta_2-t_1))dt_2dt_1 \\
&+\int_0^{\theta_1}\int_{\theta_1}^{1/2}(p^2+p(1-p)+(1-p)^2)((\theta_1-t_1)+(\theta_2-t_2))+p(1-p)((t_2-\theta_1)+(\theta_2-t_1))dt_2dt_1 \\
&+\int_{\theta_1}^{1/2}\int_{t_1}^{1/2}(p^2+p(1-p)+(1-p)^2)((t_1-\theta_1)+(\theta_2-t_2))+p(1-p)((t_2-\theta_1)+(\theta_2-t_1))dt_2dt_1 \\
&+\int_{\theta_1}^{1/2}\int_0^{\theta_1}(1-p)((t_1-\theta_1)+(\theta_2-t_2))+p((\theta_1-t_2)+(\theta_2-t_1))dt_2dt_1 \\
&+\int_{\theta_1}^{1/2}\int_{\theta_1}^{t_1}(1-p)((t_1-\theta_1)+(\theta_2-t_2))+p((t_2-\theta_1)+(\theta_2-t_1))dt_2dt_1
\end{aligned}
$$

$$Q3(\theta_1,\theta_2,p)=\frac{1}{24}(-p^2(1-2\theta_1)^2(1+4\theta_1)+6(\theta_1(-1+2\theta_1)+\theta_2)) \tag{A.3}$$

Finally, the four quadrant which has the constant probability to exchange tasks, $Pr(change) = p^2+2p(1-p)$, is determined by:

$$\begin{aligned}
Q4(\theta_1,\theta_2,p) = &\int_{1/2}^{\theta_2}\int_{0}^{\theta_1}(p^2+2p(1-p))((\theta_1-t_2)+(\theta_2-t_1))+(1-p)^2((t_1-\theta_1)+(\theta_2-t_2))dt_2dt_1\\
&+\int_{1/2}^{\theta_2}\int_{\theta_1}^{1/2}(p^2+2p(1-p))((t_2-\theta_1)+(\theta_2-t_1))+(1-p)^2((t_1-\theta_1)+(\theta_2-t_2))dt_2dt_1\\
&+\int_{\theta_2}^{1}\int_{\theta_1}^{1/2}(p^2+2p(1-p))((t_2-\theta_1)+(t_1-\theta_2))+(1-p)^2((t_1-\theta_1)+(\theta_2-t_2))dt_2dt_1\\
&+\int_{\theta_2}^{1}\int_{0}^{\theta_1}(p^2+2p(1-p))((\theta_1-t_2)+(t_1-\theta_2))+(1-p)^2((t_1-\theta_1)+(\theta_2-t_2))dt_2dt_1
\end{aligned}$$

$$Q4(\theta_1,\theta_2,p)=\frac{1}{8}(1-2\theta_1+2\theta_2-2(-2+p)p(1+2\theta_1^2+2(-2+\theta_2)\theta_2)) \tag{A.4}$$

If we put together the four equations and simplify, we get the following expression for the manager's expected cost:

$$\begin{aligned}
\mathbb{E}[C(\theta_1,\theta_2,p)] = 1+(-1+\theta_1)\theta_1+(-1+\theta_2)\theta_2+p(\frac{1}{2}+\theta_1^2\\
+(-2+\theta_2)\theta_2)-\frac{1}{6}p^2(3+4\theta_1^3-4\theta_2(3+(-3+\theta_2)\theta_2))
\end{aligned}$$

Then, minimizing the expected cost with respect to θ_1 and θ_2, we get the following first order conditions:

$$- 1 + 2\theta_1(1 + p - p^2\theta_1) = 0 \tag{A.5}$$

$$- 1 + 2p(1 + p(-1 + \theta_2))(-1 + \theta_2) + 2\theta_2 = 0 \tag{A.6}$$

Rewriting equation A.6 as:

$$-1 + 2(1 - \theta_2)(1 + p - p^2(1 - \theta_2)) = 0$$

And, comparing it with equation A.5, we conclude that $\theta_1 = 1 - \theta_2$ or $\theta_1 + \theta_2 = 1$. Thus, any equilibrium (θ_1^*, θ_2^*) of the Cost Minimization Problem with Centralized Tasks Reallocation is symmetric around the center. In other words, $\left|\frac{1}{2} - \theta_1^*\right| = \left|\theta_2^* - \frac{1}{2}\right|$.

Moreover, the optimal positions of the workers are:

$$\theta_1^*(p) = \frac{1 + p - \sqrt{(1 + 2p - p^2)}}{2p^2}$$

$$\theta_2^*(p) = 1 - \theta_1^*(p)$$

To prove that in equilibrium there is a degree of specialization, we need to prove that $0 \leq \theta_1^*(p) \leq \frac{1}{2} \leq \theta_2^*(p) \leq 1$. Given $0 \leq p \leq 1$ and taking the limits of the optimal positions, we get:

$$\lim_{p \to 1} \theta_1^*(p) = 1 - \frac{\sqrt{2}}{2} \approx 0.29$$

$$\lim_{p \to 0} \theta_1^*(p) \approx \frac{1}{2}$$

By symmetry, we know that:

$$\lim_{p \to 1} \theta_2^*(p) = 1 - \lim_{p \to 1} \theta_1^*(p) \approx 0.71$$

$$\lim_{p \to 0} \theta_2^*(p) = 1 - \lim_{p \to 0} \theta_1^*(p) \approx \frac{1}{2}$$

Also, notice that $\frac{\partial \theta_1^*(p)}{\partial p} < 0$. By symmetry again, we can define $\delta^*(p) = \frac{1}{2} - \theta_1^*(p)$ and $\frac{\partial \delta^*(p)}{\partial p} = -\frac{\partial \theta_1^*(p)}{\partial p} \geq 0$.

$\square$

Proposition 4

Proof. Define the team's probability to exchange tasks,

$$Pr[(t_1, t_2) \in T^W] = \int_{\theta_1}^{1} \int_{0}^{\theta_2} dt_2 dt_1 - \int_{\theta_1}^{\theta_2} \int_{t_1}^{\theta_2} dt_2 dt_1 - \int_{\theta_1}^{2\theta_1} \int_{0}^{2\theta_1 - t1} dt_2 dt_1 - \int_{\theta_2}^{1} \int_{2\theta_2 - t_1}^{\theta_2} dt_2 dt_1$$

Moreover, given $p = 1$, we can define the leader's probability to exchange tasks as follows,

$$Pr[(t_1, t_2) \in T^W] = \int_{\theta_1}^{1} \int_{0}^{\theta_2} dt_2 dt_1 - \int_{\theta_1}^{\theta_2} \int_{t_1}^{\theta_2} dt_2 dt_1$$

Then,

$$\begin{aligned} I(\theta_1, \theta_2) &= \int_{\theta_1}^{2\theta_1} \int_{0}^{2\theta_1 - t1} dt_2 dt_1 + \int_{\theta_2}^{1} \int_{2\theta_2 - t_1}^{\theta_2} dt_2 dt_1 \\ &= \frac{1}{2}(1 + \theta_1^2 - 2\theta_2 + \theta_2^2)) \end{aligned}$$

Using the symmetric condition, $I(\delta) = \frac{1}{4} + \delta(\delta - 1) \geq 0$ because $\delta \in [0, 1/2]$. Finally, $\lim_{\delta -> 1/2} I(\delta) = 0$, $\lim_{\delta -> 0} I(\delta) = 1/4$ and $I'(\delta) \leq 0$. $\square$

Proposition 5

Proof. Consider the worker in position θ_1 in the Figure A.2. Let us assume that the worker knows his position θ_1, the position of the other worker θ_2 and the realization of his task t_1^0. The worker can identify in which realizations of tasks (t_1, t_2), he is willing to exchange tasks. Given t_1^0, the worker θ_1 would like to exchange tasks when t_2^0 falls in the interval determined by his task realization and the mirror of it on the line. The mirror point is $2\theta_1 - t_1^0$. Note that the mirror point could be greater or lower than zero. In a symmetric fashion, the worker in the position θ_2

is willing to exchange tasks if t_1^0 falls in the interval between t_2^0 and $2\theta_2 - t_2^0$. The mirror value in this second case could be greater or lower than 1[1].

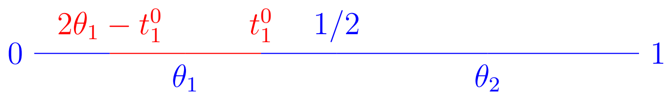


Figure A.2: Interval for the t_2^0 where the worker in the position θ_1 is willing to exchange tasks

If we joint the situations where workers would like to exchange tasks given their positions, we can classified those situations in four different cases. The workers would like to exchange tasks when:

- If $\theta_2 \geq t_1 \geq \theta_1$, $\theta_1 \leq t_2 \leq \theta_2$ and $t_2 \leq t_1$.
- If $t_1 \geq \theta_2$, $\theta_1 \leq t_2 \leq \theta_2$ and $t_2 \leq \theta_2 \leq t_1 \leq min(1, 2\theta_2 - t_2)$.
- If $\theta_2 \geq t_1 \geq \theta_1$, $t_2 \leq \theta_1$ and $max(0, 2\theta_1 - t_1) \leq t_2 \leq \theta_1 \leq t_1$.
- If $t_1 \geq \theta_2$, $t_2 \leq \theta_1$, $t_2 \leq \theta_2 \leq t_1 \leq min(1, 2\theta_2 - t_2)$ and $max(0, 2\theta_1 - t_1) \leq t_2 \leq \theta_1 \leq t_1$.

The realizations of (t_1, t_2) fulfilling the four conditions above are depicted in Figure A.3. Figure A.3 represents task t_1 in the horizontal axis and t_2 in the vertical axis. In the white area, at least one of the workers is not willing to exchange tasks and in the blue one both of them are willing to exchange tasks (unanimity voting rule). Three inequalities determine the region where the workers would like to exchange: 1) $t_2 \leq t_1$, 2) $t_2 \geq 2\theta_1 - t_1$ and 3) $t_2 \leq 2\theta_2 - t_1$. The first one is determined by the $45°$ line and the other two by the limits of the interval in which the workers are willing to exchange. Next, consider the binding equations characterizing inequalities 2 and 3. Those equations are orthogonal to the $45°$ line and are parallel between them. Moreover, the intersections of them with the $45°$ line are exactly the positions of the workers on the line. If we move the workers' positions closer to each other, those lines also get closer. At the extreme, those lines overlap completely. Then, there would not be a region where the workers would like to exchange. On the contrary, If the leader places the workers at the extremes of the line, the probability of tasks reallocation increases until $1/2$.

[1]There is neither a case where the mirror point of the interval of the worker in position θ_1 is higher than 1 nor a case where the mirror point of the interval of the worker in the position θ_2 is lower than zero given the Assumption 2 made.

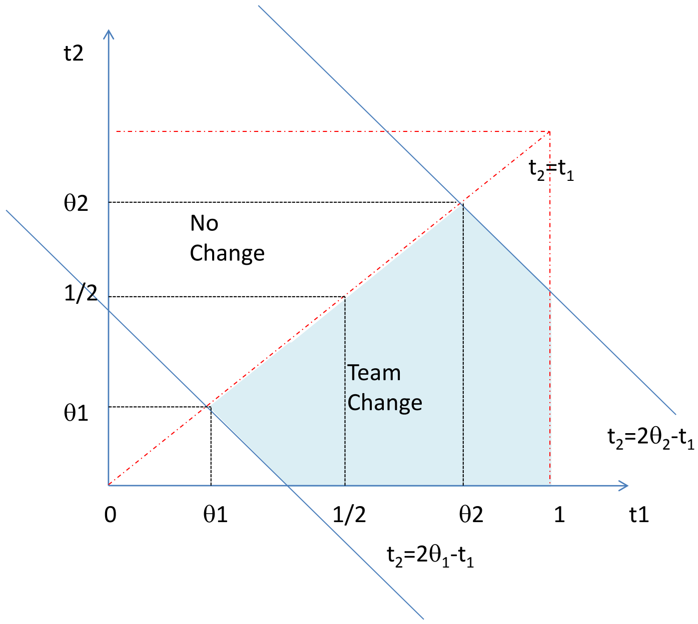


Figure A.3: Team Task Reallocation Region

The problem of the manager in a decentralized organization is to find the positions of the workers on the line in order to minimize her expected cost. So, we divide the minimization problem of the manager in four subproblems given the different constraints on the positions of the workers we studied previously. In each case, we calculate the optimal positions and we compare them in order to determine the global minimum. The cases we have identify are the following:

- Case I: If $2\theta_1 \leq \theta_2$ and $2\theta_2 - 1 \geq \theta_1$:

$$\mathbb{E}[C_1(\theta_1, \theta_2)] = Nochange(\theta_1, \theta_2) + Change_1(\theta_1, \theta_2)$$

- Case II: If $2\theta_1 > \theta_2$ and $2\theta_2 - 1 < \theta_1$:

$$\mathbb{E}[C_2(\theta_1, \theta_2)] = Nochange(\theta_1, \theta_2) + Change_2(\theta_1, \theta_2)$$

- Case III: If $2\theta_1 \leq \theta_2$ and $2\theta_2 - 1 < \theta_1$:

$$\mathbb{E}[C_3(\theta_1,\theta_2)] = Nochange(\theta_1,\theta_2) + Change_3(\theta_1,\theta_2)$$

- Case IV: If $2\theta_1 > \theta_2$ and $2\theta_2 - 1 \geq \theta_1$:

$$\mathbb{E}[C_4(\theta_1,\theta_2)] = Nochange(\theta_1,\theta_2) + Change_4(\theta_1,\theta_2)$$

where each expected cost function is divided on two different parts: 1) the expected cost if the workers decided not to exchange tasks, $Nochange$; 2) the expected cost if the workers decided to exchange tasks, $Change_i$, where $i = 1, ..., 4$. Now, we will specify their functional forms.

The equation that determines where the workers would not like to exchange has the same specification for all the four cases and it is:

$$\begin{aligned} NoChange(\theta_1,\theta_2) = &\int_0^{\theta_1}\int_0^{\theta_2}(\theta_1 - t_1) + (\theta_2 - t_2)dt_2dt_1 + \int_0^{\theta_1}\int_{\theta_2}^{1}(\theta_1 - t_1) + (t_2 - \theta_2)dt_2dt_1 \\ &+ \int_{\theta_1}^{1}\int_{\theta_2}^{1}(t_1 - \theta_1) + (t_2 - \theta_2)dt_2dt_1 + \int_{\theta_1}^{2\theta_1}\int_0^{2\theta_1 - t_1}(t_1 - \theta_1) + (\theta_2 - t_2)dt_2dt_1 \\ &+ \int_{\theta_1}^{\theta_2}\int_{t_1}^{\theta_2}(t_1 - \theta_1) + (\theta_2 - t_2)dt_2dt_1 + \int_{\theta_2}^{1}\int_{2\theta_2 - t_1}^{\theta_2}(t_1 - \theta_1) + (\theta_2 - t_2)dt_2dt_1 \end{aligned}$$

$$NoChange(\theta_1,\theta_2) = \frac{1}{6}(9 - 2\theta_1^3 + 6\theta_1^2(1+\theta_2) - 3\theta_1(3 + 2(-2+\theta_2)\theta_2) + \theta_2(-15 + 2\theta_2(3+\theta_2))) \tag{A.7}$$

On the other hand, the expression that determines where the workers would like to exchange is conditioned by the constraints. As a consequence, we would identify each expression and we would solve each of the problems:

- Case I: This is for $2\theta_1 \leq \theta_2$ and $2\theta_2 - 1 \geq \theta_1$: Let us define the equation $Change_1$,

$$Change_1(\theta_1,\theta_2) = \int_{\theta_1}^{\theta_2}\int_{\theta_1}^{t_1}(t_2-\theta_1)+(\theta_2-t_1)dt_2dt_1 + \int_{\theta_1}^{2\theta_1}\int_{2\theta_1-t_1}^{\theta_1}(\theta_1-t_2)+(\theta_2-t_1)dt_2dt_1$$
$$+\int_{\theta_1}^{\theta_2}\int_{0}^{\theta_1}(\theta_1-t_2)+(\theta_2-t_1)dt_2dt_1 + \int_{\theta_2}^{1}\int_{0}^{\theta_1}(\theta_1-t_2)+(t_1-\theta_2)dt_2dt_1$$
$$+\int_{\theta_2}^{1}\int_{\theta_1}^{2\theta_2-t_1}(t_2-\theta_1)+(t_1-\theta_2)dt_2dt_1$$

$$Change_1(\theta_1,\theta_2) = -\theta_1^2(-1+\theta_2)+\frac{1}{6}(-1+3\theta_2)+\theta_1(1/2+(-2+\theta_2)\theta_2) \quad \text{(A.8)}$$

Then, the minimization problem of the total expected cost is:

$$\begin{aligned} Min.[\mathbb{E}[C_1(\theta_1,\theta_2)] &= Nochange(\theta_1,\theta_2)+Change_1(\theta_1,\theta_2)] \\ &= \frac{1}{3}(4-\theta_1(3+(-6+\theta_1)\theta_1)+\theta_2(-6+\theta_2(3+\theta_2))) \\ &s.t.\ 2\theta_1 \le \theta_2 \ and\ 2\theta_2-1 \ge \theta_1 \end{aligned}$$

The Langrangian function is:

$$L_1(\theta_1,\theta_2) = \frac{1}{3}(4-\theta_1(3+(-6+\theta_1)\theta_1)+\theta_2(-6+\theta_2(3+\theta_2)))-\lambda_1(2\theta_1-\theta_2)-\lambda_2(\theta_1+1-2\theta_2)$$

The first order conditions with respect to the positions are:

$$\theta_1(\frac{\partial L_1}{\partial \theta_1}) = \theta_1\left(-1+4\theta_1-\theta_1^2-2\lambda_1-\lambda_2\right)=0$$

$$\theta_2(\frac{\partial L_1}{\partial \theta_2}) = \theta_2\left(-2+2\theta_2+\theta_2^2+\lambda_1+2\lambda_2\right)=0$$

Assuming that the constraints are not binding, the local minimum of L_1 are the positions $(0.27, 0.73)$. On the contrary is the two constraints were binding the unique solution is

$(1/3, 2/3)$. In the case where only the first constraint holds with equality, the optimal position for the leader are $(0, 1/2)$ and finally if only the second constraint is binding the optimal positions are $(0.34, 0.69)$. Comparing the total expected cost in each of this optimal points we show that the interior solution $(0.27, 0.73)$ is the minimum among them.

- Case II: If $2\theta_1 > \theta_2$ and $2\theta_2 - 1 < \theta_1$: Let us define the equation $Change_2$,

$$\begin{aligned} Change_2(\theta_1,\theta_2) = & \int_{\theta_1}^{\theta_2}\int_{\theta_1}^{t_1}(t_2-\theta_1)+(\theta_2-t_1)dt_2dt_1 + \int_{\theta_1}^{\theta_2}\int_{2\theta_1-t_1}^{\theta_1}(\theta_1-t_2)+(\theta_2-t_1)dt_2dt_1 \\ & + \int_{\theta_2}^{2\theta_1}\int_{2\theta_1-t_1}^{\theta_1}(\theta_1-t_2)+(t_1-\theta_2)dt_2dt_1 + \int_{\theta_2}^{2\theta_1}\int_{\theta_1}^{2\theta_2-t_1}(t_2-\theta_1)+(t_1-\theta_2)dt_2dt_1 \\ & + \int_{2\theta_1}^{2\theta_2-\theta_1}\int_{0}^{\theta_1}(\theta_1-t_2)+(t_1-\theta_2)dt_2dt_1 + \int_{2\theta_1}^{2\theta_2-\theta_1}\int_{\theta_1}^{2\theta_2-\theta_1}(t_2-\theta_1)+(t_1-\theta_2)dt_2dt_1 \\ & + \int_{2\theta_2-\theta_1}^{1}\int_{0}^{2\theta_2-t_1}(\theta_1-t_2)+(t_1-\theta_2)dt_2dt_1 \end{aligned}$$

$$Change_2(\theta_1,\theta_2) = \frac{1}{2}(-1-\theta_1-6\theta_1^3+(5+2\theta_1(2+5\theta_1))\theta_2-2(4+5\theta_1)\theta_2^2+6\theta_2^3) \tag{A.9}$$

Then, the minimization problem of the total expected cost is:

$$\begin{aligned} Min.[\mathbb{E}[C_2(\theta_1,\theta_2)] &= Nochange(\theta_1,\theta_2) + Change_2(\theta_1,\theta_2)] \\ &= 1-2\theta_1+\theta_1^2-(10\theta_1^3)/3+2\theta_1(2+3\theta_1)\theta_2-3(1+2\theta_1)\theta_2^2+(10\theta_2^3)/3 \\ & s.t.\ 2\theta_1 > \theta_2\ and\ 2\theta_2 - 1 < \theta_1 \end{aligned}$$

The Langrangian function is:

$$L_2(\theta_1,\theta_2) = 1-2\theta_1+\theta_1^2-(10\theta_1^3)/3+2\theta_1(2+3\theta_1)\theta_2-3(1+2\theta_1)\theta_2^2+(10\theta_2^3)/3-\lambda_1(\theta_2-2\theta_1)-\lambda_2(2\theta_2-\theta_1$$

The first order conditions with respect to the positions are:

$$\theta_1(\frac{\partial L_2}{\partial \theta_1}) = \theta_1\left(-2+4\theta_2+2(\theta_1-5\theta_1^2+6\theta_1\theta_2-3\theta_2^2)+2\lambda_1+\lambda_2\right) = 0$$

$$\theta_2(\frac{\partial L_2}{\partial \theta_2}) = \theta_2\left(6\theta_1^2+\theta_1(4-12\theta_2)+2\theta_2(-3+5\theta_2)-\lambda_1-2\lambda_2\right) = 0$$

The interior solution in this case is $(1/2, 1/2)$. There are also other corner solutions but again all these solutions are dominated by the interior solution of L_1.

- Case III: If $2\theta_1 \leq \theta_2$ and $2\theta_2 - 1 < \theta_1$: Let us define the equation $Change_3$,

$$\begin{aligned} Change_3(\theta_1,\theta_2) = & \int_{\theta_1}^{\theta_2}\int_{\theta_1}^{t_1}(t_2-\theta_1)+(\theta_2-t_1)dt_2dt_1 + \int_{\theta_1}^{2\theta_1}\int_{2\theta_1-t_1}^{\theta_1}(\theta_1-t_2)+(\theta_2-t_1)dt_2dt_1 \\ & + \int_{2\theta_1}^{\theta_2}\int_{0}^{\theta_1}(\theta_1-t_2)+(\theta_2-t_1)dt_2dt_1 + \int_{\theta_2}^{2\theta_2-\theta_1}\int_{0}^{\theta_1}(\theta_1-t_2)+(t_1-\theta_2)dt_2dt_1 \\ & + \int_{\theta_2}^{2\theta_2-\theta_1}\int_{\theta_1}^{2\theta_2-\theta_1}(t_2-\theta_1)+(t_1-\theta_2)dt_2dt_1 + \int_{2\theta_2-\theta_1}^{1}\int_{0}^{2\theta_2-t_1}(\theta_1-t_2)+(t_1-\theta_2)dt_2dt_1 \end{aligned}$$

$$Change_3(\theta_1,\theta_2) = \frac{1}{6}(-3-3\theta_1-2\theta_1^3+3(5+2\theta_1(2+\theta_1))\theta_2-6(4+3\theta_1)\theta_2^2+16\theta_2^3) \tag{A.10}$$

Then, the minimization problem of the total expected cost is:

$$\begin{aligned}
Min.[\mathbb{E}[C_3(\theta_1,\theta_2)] &= Nochange(\theta_1,\theta_2) + Change_3(\theta_1,\theta_2)] \\
&= 1 - 2\theta_1 + \theta_1^2 - (2\theta_1^3)/3 + 2\theta_1(2+\theta_1)\theta_2 - (3+4\theta_1)\theta_2^2 + 3\theta_2^3 \\
& s.t.\ 2\theta_1 \leq \theta_2\ and\ 2\theta_2 - 1 < \theta_1
\end{aligned}$$

The Langrangian function is:

$$L_3(\theta_1,\theta_2) = 1-2\theta_1+\theta_1^2-(2\theta_1^3)/3+2\theta_1(2+\theta_1)\theta_2-(3+4\theta_1)\theta_2^2+3\theta_2^3-\lambda_1(2\theta_1-\theta_2)-\lambda_2(2\theta_2-\theta_1-1)$$

The first order conditions with respect to the positions are:

$$\theta_1(\frac{\partial L_3}{\partial \theta_1}) = \theta_1\left(-2(1+\theta_1^2+2(-1+\theta_2)\theta_2-\theta_1(1+2\theta_2)+\lambda_1)+\lambda_2\right) = 0$$

$$\theta_2(\frac{\partial L_3}{\partial \theta_2}) = \theta_2\left(2\theta_1(2+\theta_1)-6\theta_2-8\theta_1\theta_2+9\theta_2^2+\lambda_1-2\lambda_2\right) = 0$$

The interior solution in this case $(0.27, 0.71)$. There are also other corner solutions but again all these solutions are dominated by the interior solution of L_1.

- Case IV: If $2\theta_1 > \theta_2$ and $2\theta_2 - 1 \geq \theta_1$: Let us define the equation $Change_4$,

$$\begin{aligned}
Change_4(\theta_1,\theta_2) = & \int_{\theta_1}^{\theta_2}\int_{\theta_1}^{t_1}(t_2-\theta_1)+(\theta_2-t_1)dt_2dt_1 + \int_{\theta_1}^{\theta_2}\int_{2\theta_1-t_1}^{\theta_1}(\theta_1-t_2)+(\theta_2-t_1)dt_2dt_1 \\
& + \int_{\theta_2}^{2\theta_1}\int_{2\theta_1-t_1}^{\theta_1}(\theta_1-t_2)+(t_1-\theta_2)dt_2dt_1 + \int_{2\theta_1}^{1}\int_{0}^{\theta_1}(\theta_1-t_2)+(t_1-\theta_2)dt_2dt_1 \\
& + \int_{\theta_2}^{1}\int_{\theta_1}^{2\theta_2-\theta_1}(t_2-\theta_1)+(t_1-\theta_2)dt_2dt_1
\end{aligned}$$

$$Change_4(\theta_1,\theta_2) = \frac{1}{6}(-1-16\theta_1^3+3\theta_2+2\theta_2^3+6\theta_1^2(1+3\theta_2)-3\theta_1(-1+2\theta_2(2+\theta_2))) \tag{A.11}$$

Then, the minimization problem of the total expected cost is:

$$\begin{aligned} Min.[\mathbb{E}[C_4(\theta_1,\theta_2)] &= Nochange(\theta_1,\theta_2) + Change_4(\theta_1,\theta_2)] \\ &= \frac{4}{3} - 3\theta_1^3 - 2\theta_2 + \theta_2^2 + (2\theta_2^3)/3 + \theta_1^2(2+4\theta_2) - \theta_1(1+2\theta_2^2) \\ & s.t.\ 2\theta_1 > \theta_2 \ and\ 2\theta_2 - 1 \geq \theta_1 \end{aligned}$$

The Langrangian function is:

$$L_4(\theta_1,\theta_2) = \frac{4}{3} - 3\theta_1^3 - 2\theta_2 + \theta_2^2 + (2\theta_2^3)/3 + \theta_1^2(2+4\theta_2) - \theta_1(1+2\theta_2^2) - \lambda_1(\theta_2-2\theta_1) - \lambda_2(\theta_1+1-2\theta_2)$$

The first order conditions with respect to the positions are:

$$\theta_1(\frac{\partial L_4}{\partial\theta_1}) = \theta_1\left(-1-9\theta_1^2-2\theta_2^2+\theta_1(4+8\theta_2)+2\lambda_1-\lambda_2\right) = 0$$

$$\theta_2(\frac{\partial L_4}{\partial\theta_2}) = \theta_2\left(-2+4\theta_1^2-4\theta_1\theta_2+2\theta_2(1+\theta_2)-\lambda_1+2\lambda_2\right) = 0$$

There are no interior solutions in this case. There are corner solutions but again all these solutions are dominated by the interior solution of L_1.

Then, the first order conditions of the problem that minimize the expected total cost are the following:

$$-1+4\theta_1-\theta_1^2 = 0 \implies \theta_1^D = 2-\sqrt{3} \approx 0.26$$

$$-2+2\theta_2-\theta_2^2 = 0 \implies \theta_2^D = -1+\sqrt{3} \approx 0.73$$

This result also implies a symmetric solution, where $1/2 - \theta_1^D = \theta_2^D - 1/2$.

Finally, remember that for any given (θ_1, θ_2), workers would like to exchange less often than the manager would like to. If we assume that the manager has perfect information about the tasks workers received, the manager would choose the maximum level of heterogeneity given a centralized organization to take advantages of the tasks reallocation possibilities. However, those positions are less heterogeneous than the positions the manager chooses in a decentralized organization. Since the heterogeneity of the team selected by the manager decreases as p reduces, the optimal positions selected by the manger on a decentralized organization are more heterogeneous than the optimal positions in a centralized organization for all p.

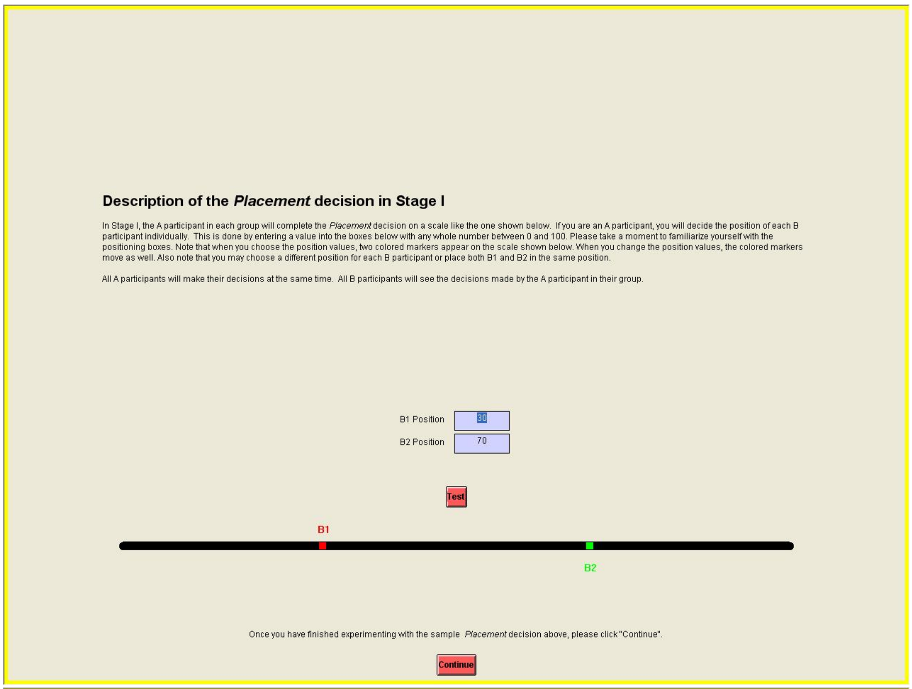
□

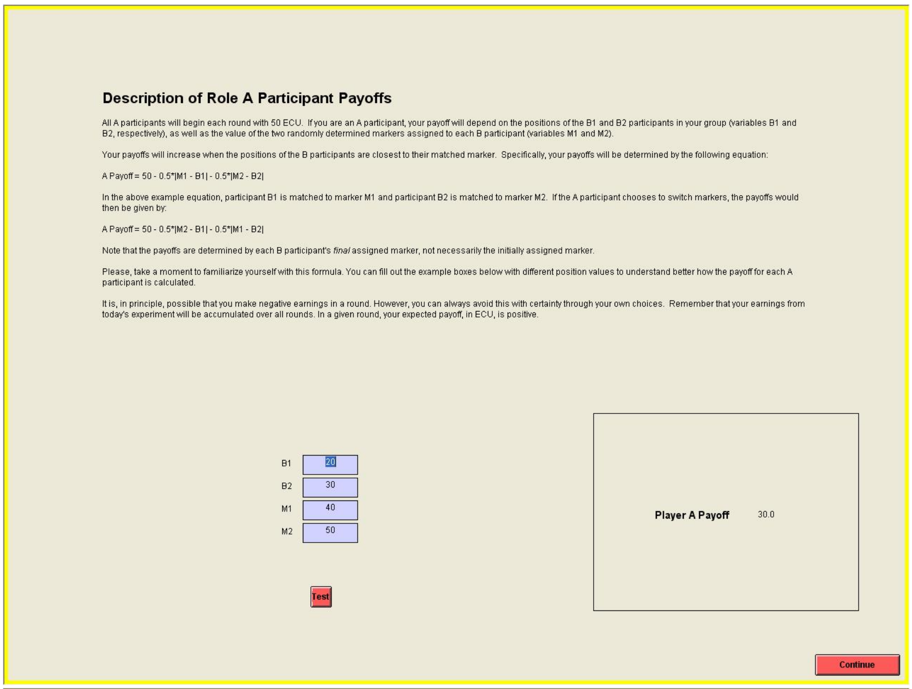
Proposition 6

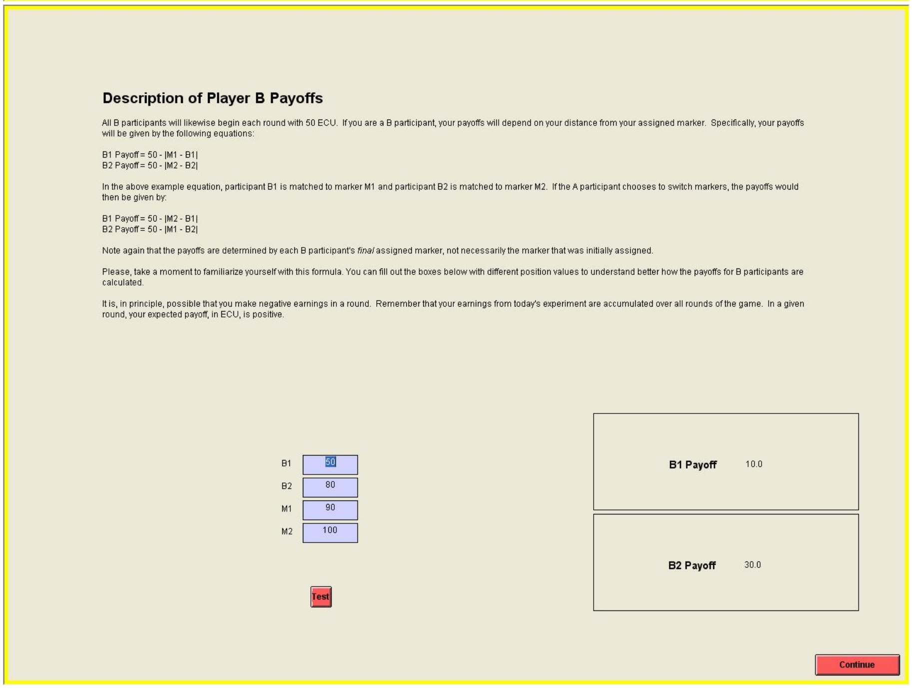
Proof. Given the optimal positions in the decentralized organizational structure - $(0.26, 0.73)$ - the expected cost of the manager in this type of organization is 0.4051. We compare this result with the expected cost the manager would obtain in the centralized organization playing the optimal positions under different values of p. Replacing the optimal positions - $\theta_1^*(p)$ and $\theta_2^*(p)$ - in the expected cost of the centralized organizational structure, we obtain an expression that is a function of p, $\mathbb{E}[C^C(p)]$. Equalizing the last expression to 0.4051, we find a $p^* = 0.82$. Moreover, $\frac{\partial \mathbb{E}[C^C(p)]}{\partial p} < 0$. Then, we can conclude that there is a p^* such that for values of $p \geq p^*$ there exists some $(\theta_1^*(p), \theta_2^*(p))$ that gives us a lower expected cost in the centralized organizational structure than in the decentralized organizational structure. Additionally, for values of $p < p^*$ do not exists some $(\theta_1^*(p), \theta_2^*(p))$ that gives us a lower expected cost in the centralized organization than in the decentralized organization.

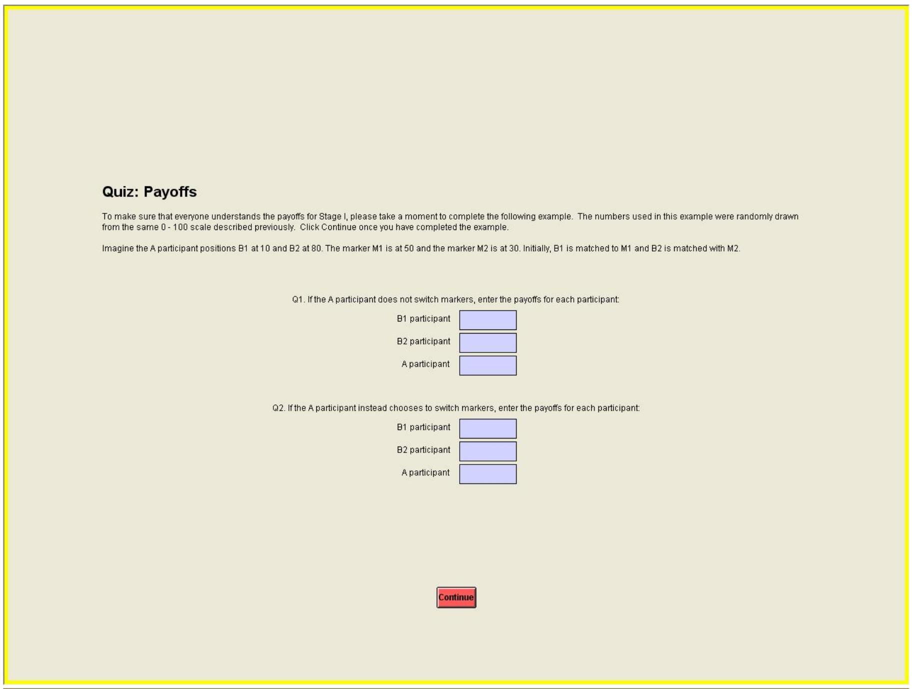
□

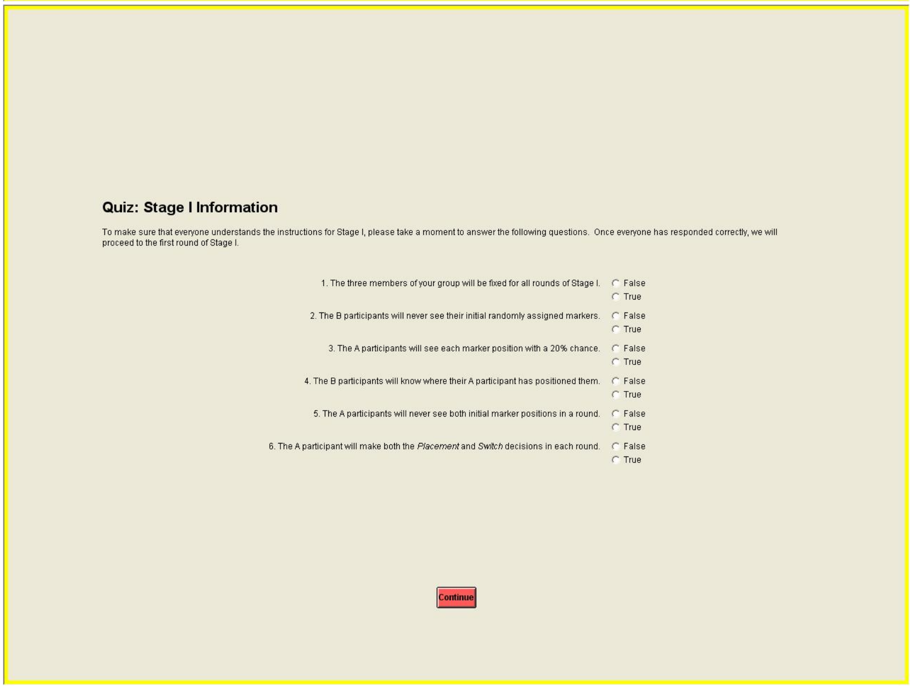
A.2 Experimental design: Screenshoots




Description of Role A Participant Payoffs
All A participants will begin each round with 50 ECU. If you are an A participant, your payoff will depend on the positions of the B1 and B2 participants in your group (variables B1 and B2, respectively), as well as the value of the two randomly determined markers assigned to each B participant (variables M1 and M2).
Your payoffs will increase when the positions of the B participants are closest to their matched marker. Specifically, your payoffs will be determined by the following equation:
A Payoff = 50 - 0.5*|M1 - B1| - 0.5*|M2 - B2|
In the above example equation, participant B1 is matched to marker M1 and participant B2 is matched to marker M2. If the A participant chooses to switch markers, the payoffs would then be given by:
A Payoff = 50 - 0.5*|M2 - B1| - 0.5*|M1 - B2|
Note that the payoffs are determined by each B participant's final assigned marker, not necessarily the initially assigned marker.
Please, take a moment to familiarize yourself with this formula. You can fill out the example boxes below with different position values to understand better how the payoff for each A participant is calculated.
It is, in principle, possible that you make negative earnings in a round. However, you can always avoid this with certainty through your own choices. Remember that your earnings from today's experiment will be accumulated over all rounds. In a given round, your expected payoff, in ECU, is positive.
B1
20
B2
30
M1
40
M2
50
Test
Player A Payoff
30.0
Continue


Description of Player B Payoffs
All B participants will likewise begin each round with 50 ECU. If you are a B participant, your payoffs will depend on your distance from your assigned marker. Specifically, your payoffs will be given by the following equations:
B1 Payoff = 50 - |M1 - B1|
B2 Payoff = 50 - |M2 - B2|
In the above example equation, participant B1 is matched to marker M1 and participant B2 is matched to marker M2. If the A participant chooses to switch markers, the payoffs would then be given by:
B1 Payoff = 50 - |M2 - B1|
B2 Payoff = 50 - |M1 - B2|
Note again that the payoffs are determined by each B participant's final assigned marker, not necessarily the marker that was initially assigned.
Please, take a moment to familiarize yourself with this formula. You can fill out the boxes below with different position values to understand better how the payoffs for B participants are calculated.
It is, in principle, possible that you make negative earnings in a round. Remember that your earnings from today's experiment are accumulated over all rounds of the game. In a given round, your expected payoff, in ECU, is positive.
B1
50
B2
80
M1
90
M2
100
Test
B1 Payoff
10.0
B2 Payoff
30.0
Continue


Quiz: Payoffs
To make sure that everyone understands the payoffs for Stage I, please take a moment to complete the following example. The numbers used in this example were randomly drawn from the same 0 - 100 scale described previously. Click Continue once you have completed the example.
Imagine the A participant positions B1 at 10 and B2 at 80. The marker M1 is at 50 and the marker M2 is at 30. Initially, B1 is matched to M1 and B2 is matched with M2.
Q1. If the A participant does not switch markers, enter the payoffs for each participant:
B1 participant
B2 participant
A participant
Q2. If the A participant instead chooses to switch markers, enter the payoffs for each participant:
B1 participant
B2 participant
A participant
Continue


Quiz: Stage I Information
To make sure that everyone understands the instructions for Stage I, please take a moment to answer the following questions. Once everyone has responded correctly, we will proceed to the first round of Stage I.
1. The three members of your group will be fixed for all rounds of Stage I.
False
True
2. The B participants will never see their initial randomly assigned markers.
False
True
3. The A participants will see each marker position with a 20% chance.
False
True
4. The B participants will know where their A participant has positioned them.
False
True
5. The A participants will never see both initial marker positions in a round.
False
True
6. The A participant will make both the *Placement* and *Switch* decisions in each round.
False
True
Continue

A.3 Country level analysis

On this appendix we present our country level analysis. Our evidence suggests that the country of origin affects the participants decisions particularly on situations with not too much not too little information.

Table 1.1 presents the results of our baseline regression from section 1.5.1 by country. Columns (2) and (4) show the estimated coefficients for the American participants. The most striking result is that the estimated coefficient of $Treatment(p = 50)_i$ is not significant anymore. It means that the probability to decentralize of the 50% treatment is not statistically different than the probability to decentralize in the 20% treatment for the American participants. The Eckel-Grossman risk aversion test and the age have a positive and significant estimated coefficients. On the other hand, columns (1) and (3) show the estimated coefficients for the Spanish participants. The treatments have a similar effect than in the results of section 1.5.1 but the control variables are not significant anymore.

In Figure A.4, we calculate the predicted probability to decentralize taking the other variables at their mean values. First, notice that the predicted probability to decentralize have the same decreasing pattern as in the general case for both countries. However, the biggest reduction on this probability takes place in different points in the two countries. In US the main reduction is in the comparison between the 50% and 80% treatment. Whereas in Spain the main reduction is in the comparison between the 20% and 50% treatment. The latter is suggestive evidence that there is threshold level determining the decisions of the participants but this threshold could vary among countries. The American participants decentralize more than the Spanish participants in the 50% treatment. This evidence suggest that cultural differences can affect the threshold levels determining the selection of an organizational structure. Bloom et. al. (2012) found that social capital proxied by trust increases aggregate productivity of countries affecting the organization of the firms. In particular, they found that countries with more trust have more decentralized firms. Beyond the fact that they do not have Spain in their sample, US has higher level of trust than other Mediterranean European countries as Portugal, France, Greece and Italy.

Departing from the SOS classification, we obtain a graphical comparison by treatment and country of the proportions of centralizers, neutral players and decentralizers on Figure A.5. We get similar conclusions to those explained before in the regressions by country. We observe a reduction in the number of decentralizers as the level of information improves in both countries with higher values in US in all the treatments. There is a smoother reduction in US than in Spain where we observe a big decline between the 20% and 50% treatments. On the other hand, the

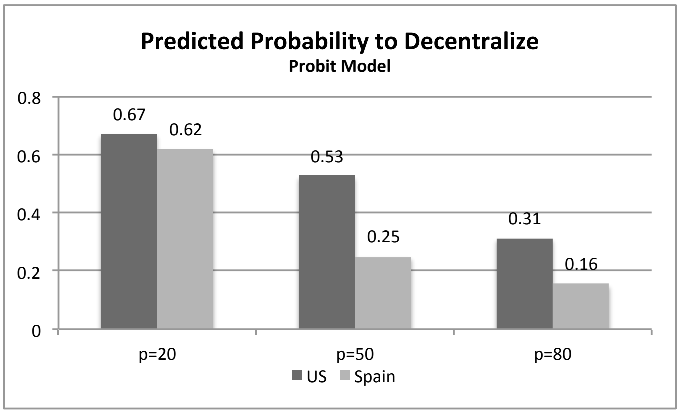
CLUSTERED BY SUBJECT

	Spain (1)	US (2)	Spain (3)	US (4)
$Treatment(p=50)_i$	-0.871***	-0.068	-0.975***	-0.374
	(0.32)	(0.30)	(0.30)	(0.32)
$Treatment(p=80)_i$	-1.313***	-0.673*	-1.312***	-0.929***
	(0.30)	(0.34)	(0.32)	(0.34)
EG_i			0.098	0.266***
			(0.12)	(0.09)
CRT_i			0.214	-0.164
			(0.15)	(0.14)
$Male_i$			-0.326	0.371
			(0.30)	(0.29)
Age_i			0.040	0.409*
			(0.15)	(0.25)
$Constant$	0.390	0.109	-0.049	-1.561***
	(0.26)	(0.26)	(0.49)	(0.60)
$`RoundDummies'$	Yes	Yes	Yes	Yes
N	672	752	672	752

Notes. * p-value< 0.1; ** p-value<0.05; *** p-value<0.01. The table provides baseline estimates of the main identification equation with and without controls by country. Standard Errors are clustered by subject. All the regressions are probit models.

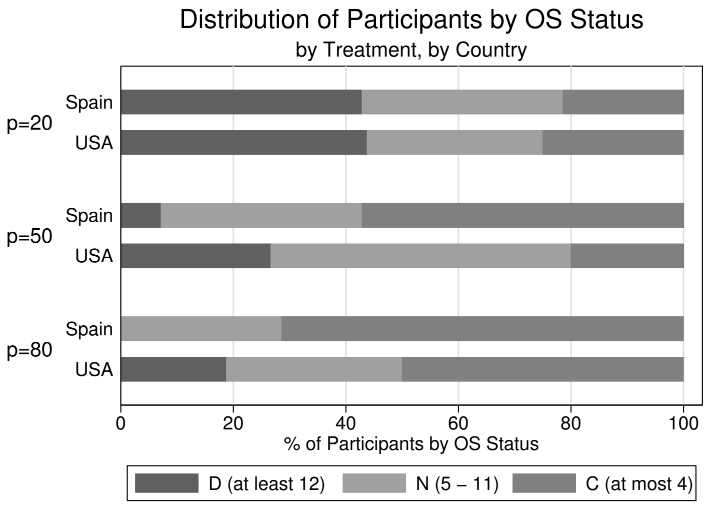
Table A.1: Organizational Structure Decision by Country

number of centralizers shows us a mirror pattern except that we observe a big increment in the number of centralizers in US between the 50% and 80% treatments given the large amount of neutral players in the US in the 50% treatment.



Notes. The figure plots the predicted probability to decentralize by treatment in each country. The predicted effect is based on the probit estimation controlling by different characteristics of each participant and clustered by subject. The results are similar using other specifications.

Figure A.4: Predicted Probability to Decentralize



Notes. The figure plots the percentage of participants in the different Organizational Structure Status that we have defined as decentralizers, random players and centralizers. The definition is based on the number of rounds that each participant decided to use an organizational structure in the Selector Stage. Each A participant played 16 rounds in the Selector stage.

Figure A.5: Distribution of Participants by Organizational Structure Status

A.4 Stability on organizational structure: An alternative classification

In this section of the appendix, we use the pattern around the modes in Figure 1.7 to classify the participants in 5 different categories in terms of their stability in the selection of an organizational structure (SOS_5). We consider that a manager is a strong centralizer (SC) if she decides to centralize in at least 14 rounds of the "Selector" Stage. A manager is a weakly centralizer (WC) if she decides to centralize between 11 and 13 rounds. She is a neutral player (N) if she decided to centralize between 6 and 10 rounds. Manager is weakly decentralizer (WD) is she decides to centralize between 3 and 5 rounds and she is a strong decentralizer if she centralize in at most 2 rounds. Table A.2 shows us the distribution of participants by treatment given this classification:

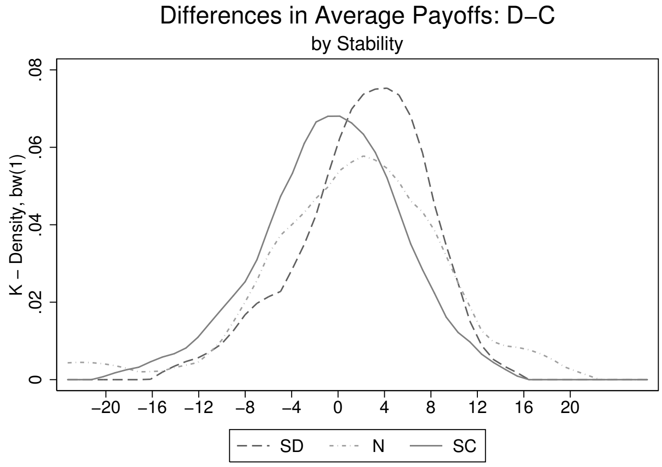
Classification/Treatment	p=20	p=50	p=80	Total
SD	10	4	3	17
WD	4	1	0	5
N	8	10	7	25
WC	5	6	3	14
SC	3	8	17	28

Notes. The figure plots the number of participants given their classification on the stability on organizational structure.

Table A.2: Participants distribution by Stability on Organizational Structure

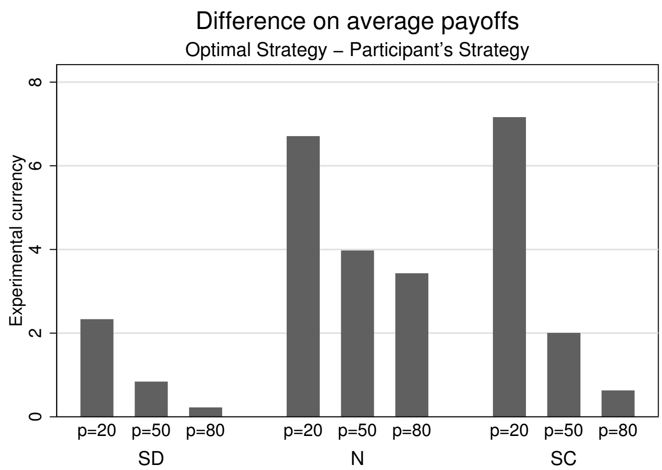
Notice that there is a concentration on participants in the diagonal of the table. There are more strong decentralizers in the 20% treatment, more neutral players in the 50% treatments and more strong centralizers in the 80% treatment. We observe how the mass of participants concentrated in each category shift by treatment. Fisher's exact test gives us a p-value of 0.004. The treatment is important to determine the proportion of participants in each of the SOS_5 categories.

We replicate the payoffs analysis with the SOS_5 category:



Notes. This graph plots a linear approximation to the distribution of the difference between average payoffs obtained by each participant on the first two stages. We subtract the participant's average payoffs on the centralized stage from the participant's average payoffs on the decentralized stage. We divide our sample in terms of the stability on the organizational structure. We consider only the participants on the managerial role.

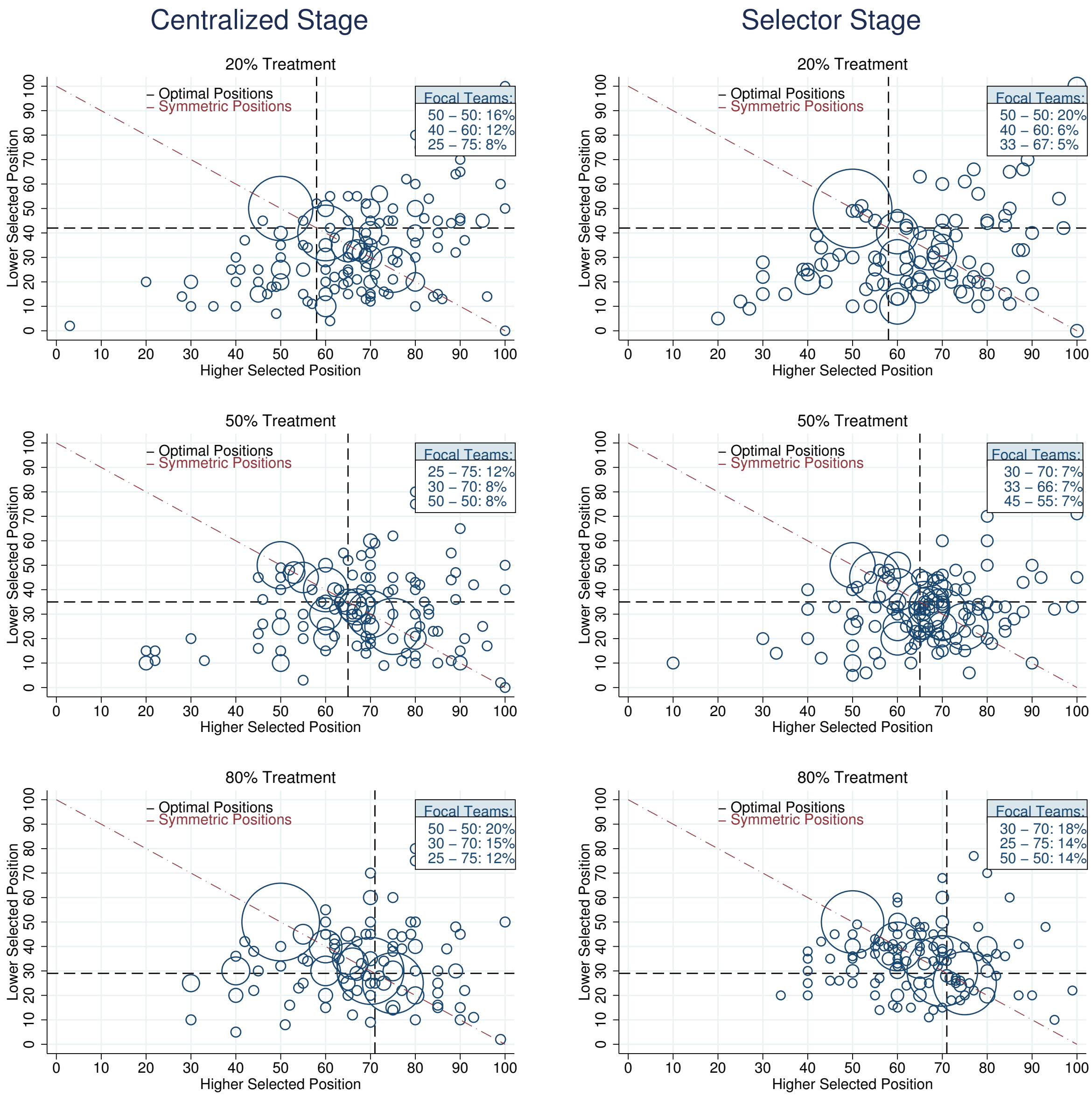
Figure A.6: Distribution of the difference on average payoffs among organizational structures



Notes. This graph plots the average difference per round per participant of the payoffs obtained playing the optimal decentralized strategy and the real payoffs obtained by the participants during the experiment on the selector stage. We separate the sample according to the classification of the participants depending on their stability on the organizational structure decision of Table 8. We consider only the participants on the managerial role.

Figure A.7: Difference on average payoffs: Optimal strategy - participant's strategy

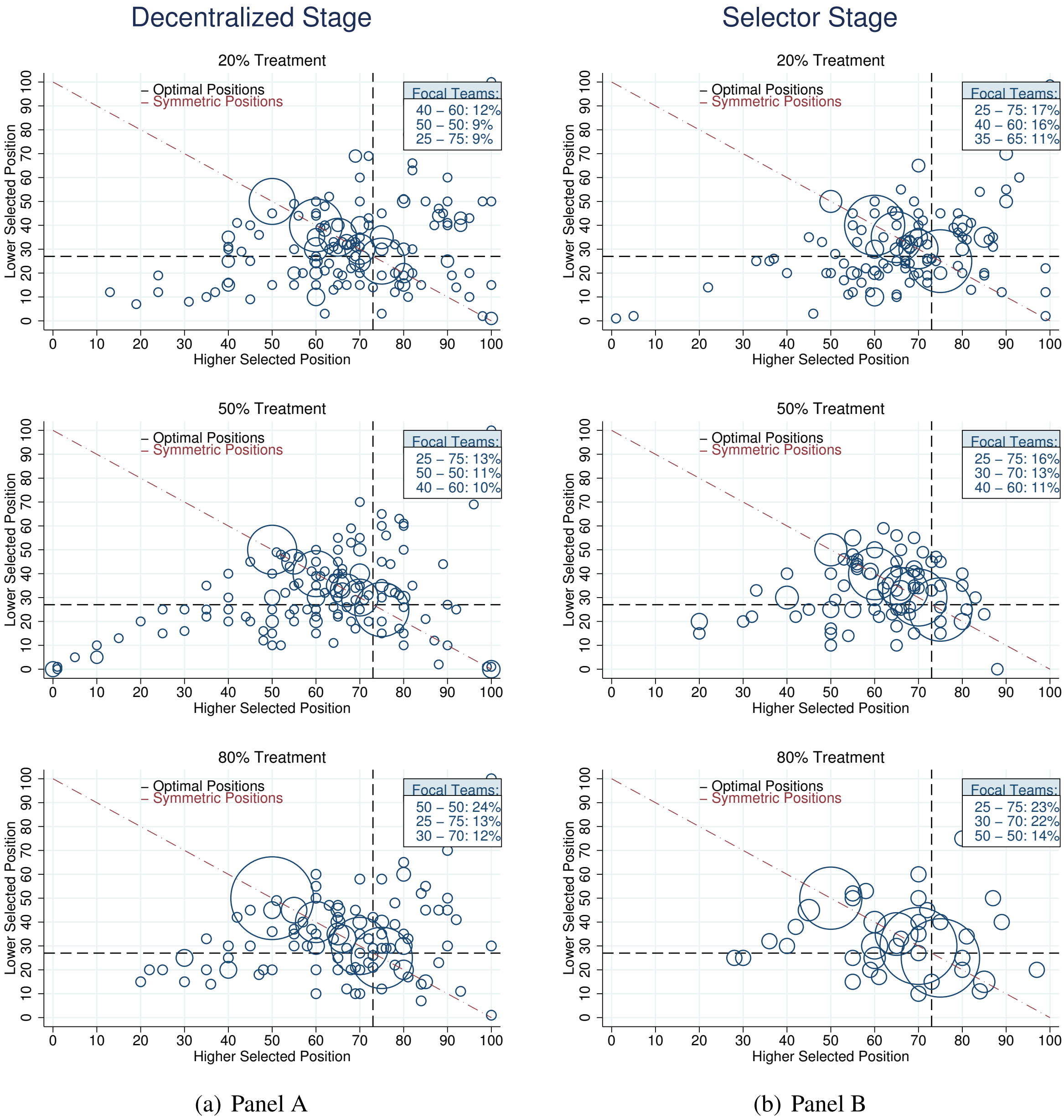
A.5 Team heterogeneity and decentralization



(a) Panel A (b) Panel B

Notes. Plot the team composition selected on the centralized rounds played by stage and treatment. The x-axis represents the right-most worker, while the y-axis represents the left-most worker per team. The size of the bubble are determined by the weight that team composition have on each treatment-stage subgroup. The dotted black lines are the optimal positions predicted by the model on centralized organizations given the level of information. The inverse red dash-dot diagonal represents the team compositions that are symmetric around the expected ex-ante task.

Figure A.8: Team Composition on the Centralized Rounds



Notes. Plot the team composition selected on the decentralized rounds played by stage and treatment. The x-axis represents the right-most worker, while the y-axis represents the left-most worker per team. The size of the bubble are determined by the weight that team composition have on each treatment-stage subgroup. The dotted black lines are the optimal positions predicted by the model on decentralized organizations given the level of information. The inverse red dash-dot diagonal represents the team compositions that are symmetric around the expected ex-ante task.

Figure A.9: Team Composition on the Decentralized Rounds

A.6 The analysis of the zero distance between positions

CENTRALIZED AND DECENTRALIZED STAGE BY TREATMENT

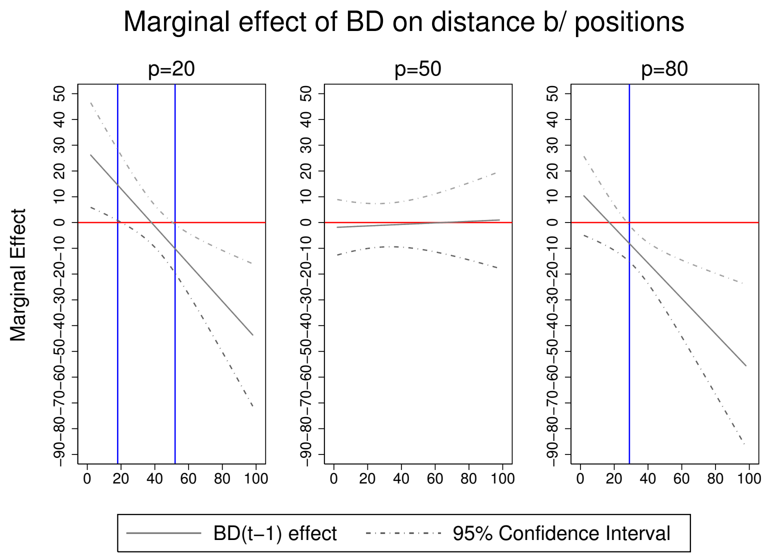
	Cen 20	Dec 20	Cen 50	Dec 50	Cen 80	Dec 80
Number of Observations						
Inmediate LA	10	7	6	7	7	12
Prolonged LA	26	9	8	24	11	16
50 then split	11	10	6	6	5	12
Fix 50	10	10	10	0	40	40
Others	4	3	2	16	9	10
Total	51	32	26	46	65	78
Percentages of the Total						
Immediate LA	20%	22%	23%	15%	11%	15%
Prolonged LA	51%	28%	31%	52%	17%	21%
50 then split	22%	31%	23%	13%	8%	15%
Fix 50	20%	31%	38%	0%	62%	51%
Others	8%	9%	8%	35%	14%	13%
Sub - Total without fix 50	41	22	16	46	25	38
Percentages of the Sub - Total						
Immediate LA	24%	32%	38%	15%	28%	32%
Prolonged LA	63%	41%	50%	52%	44%	42%
50 then split	27%	45%	38%	13%	20%	32%
Others	10%	14%	13%	35%	36%	26%

Notes. In this table we make a classification of the cases where the participants selects the same position for their team members. In 90% of the cases they select the expected task, 50. We identify the cases of immediate loss aversion as the situations where the participants choose a complete homogeneous team after a payoffs lower than 25 in the previous round. The observations we included as prolonged loss aversion take under consideration the number of periods the participants keep choosing a complete homogeneous team after experience a loss. The observations counted as prolonged loss aversion includes those in the immediate loss aversion. We also have the participants assigning a 50-50 positions to their members since the first round but then they split the positions in some of the rounds. Finally, we have those participants that always play 50-50 does not matter the results in all the rounds. We present the percentages over all the observations and the percentages without considering the participants with a fix strategy.

Table A.3: Classification of the zero distance between positions

A.7 50-50 teams: conflict of interest and mistakes

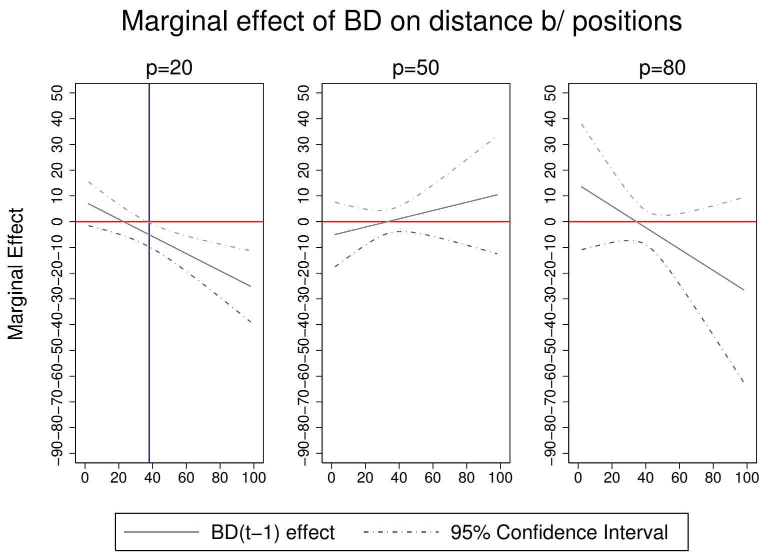
In this appendix we complement our findings on the existence of “50-50 teams” of section 1.5.2. The measure of loss we used on the section 1.5.2. depended on the observed payoffs the previous period. However, the structure of the game and the informational differences among managers and workers can play a very important role on the reactions of the participants. In particular, in the decentralized stage, workers may have a conflict of interest with their managers leading them to make decision against the managers’ objective. Those decision would be observed by the manager with some probability depending the treatment. How the managers react when their workers make a decision she does not like? In Figure A.10 we find the answer. In this situation, the dummy capturing the loss take the value of one when the workers make a decision that reduce the managers’ payoffs. This type of behavior is observed in 12% of the rounds played in the decentralized stage.



Notes. This graph plots the marginal effect associated with the fact that the switch decision was against the A participant interest in the round $t-1$ when the average distance between the position selected in the previous round was X. There is one graph for the decentralized stage in each treatment. In the decentralized organization the switch decision is an B participant task. In the x-axis we find the average distance between positions played in round $t-1$. In the y-axis we find the marginal effect. For instance, if the marginal effect is -10 in the 20% treatment when the distance played by a participant in round t-1 was 60, it implies that the participant will play a distance of 50 in round t. We also plot the confidence intervals at 95% level. The vertical blue lines specify separate the areas in the graph where we have significance effects from the areas where we do not.

Figure A.10: 50-50 teams: Decentralized stage (B against A)

Figure A.10 presents some similarities with Figure 1.13 but they are not exactly the same. Again, we observed the decreasing marginal effect in the 20% and 80% treatments and a no effect on the 50% treatment. However, there are significantly effects in 20% and 80% treatment. The marginal effects of a decision against the managers' interest in the previous round are significant in the 80% treatment for values above 28. It includes 47% of the cases. So, we still have a reduction in the heterogeneity of the team selected when the average distance in the previous period was high enough and the managers experience a loss. But, in this case we have a significance effect as well in the 20% treatment. For values above 52, we have a significant contraction in the distance played by the managers if the workers made a selection against their interest. On the contrary, for values below 19, we have a significant increment in the distance played by the managers if the workers made a selection against their interest. In the 20% treatment, 12% of the cases are below 19 and 10% of the cases are above 52.



Notes. This graph plots the marginal effect associated with the fact that the switch decision was against the A participant interest in the round $t-1$ when the average distance between the position selected in the previous round was X. There is one graph for the centralized stage in each treatment. In the centralized organization the switch decision is an A participant task. In the x-axis we find the average distance between positions played in round $t-1$. In the y-axis we find the marginal effect. For instance, if the marginal effect is -10 in the 20% treatment when the distance played by a participant in round t-1 was 60, it implies that the participant will play a distance of 50 in round t. We also plot the confidence intervals at 95% level. The vertical blue line separates the areas in the graph where we have significance effects from the areas where we do not.

Figure A.11: 50-50 teams: Centralized Stage (A against A)

Figure A.11 repeat the analysis for the centralized stage with a similar measure as that we used in Figure A.10. However, this measure have a different interpretation. In the centralized stage, the managers decide positions and tasks reallocation. Then, any decision against the managers' interest is a mistake of the same manager. This type of behavior is observed in 16% of the rounds played in the centralized stage. However, unlike the decentralized stage, this measure is not equally divided between treatments. Those cases are more concentrated in the 20% treatment and then it decreases as the information gets better. The reason is that as the information improves the A participants make less mistakes. The marginal effect is only significant in the 20% treatment above 38. The result is pretty similar to the results we found with the former loss measure.

Appendix B

APPENDIX: CHAPTER 2

B.1 Working day Schedule

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.1: Worker's Typical Working Day

B.2 Additional Results

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.2: Own and Coworkers' Hens' Age and Productivity:

	Daily Number of Eggs per Hen, y_i			
	(1) Non-replacement Weeks	(2) Replacement Weeks	(3)	(4)
Coworkers' Eggs per Hen, $\bar{y}_{-i}$	-0.31800***	-0.32766**	-0.18025*	-0.28353***
	(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

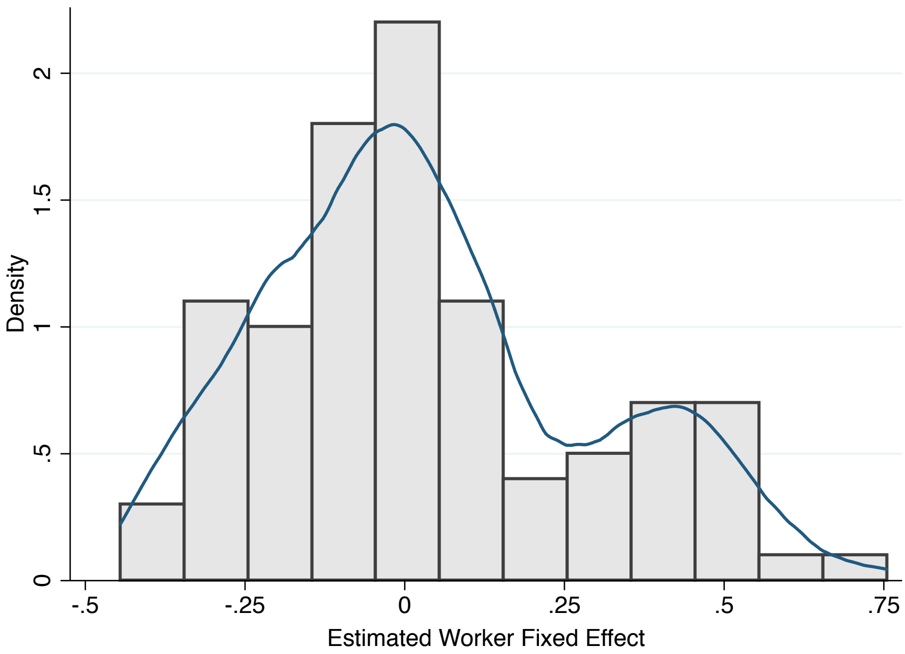
Notes. (* p-value<0.1; ** p-value<0.05; *** p-value<0.01) 2SLS estimates. Sample is restricted to all production units in sheds with at least one other production unit. Two-way clustered standard errors, with residuals grouped along both shed and day. Subsample in (1) contains observations belonging 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.3: Batch Replacement and Further Robustness Checks

	Daily Number of Eggs per Hen, y_i					
	(1) Low Prod. Age	(2) High Prod. Age	(3) Coworker is Friend	(4) Coworker is Not Friend	(5) Experience $>$ Median	(6) Experience $<$ Median
Coworkers'	-0.26615***	-0.12017	-0.19371**	-0.30046***	-0.47681***	-0.33110***
Eggs per Hen, $\bar{y}_{-i}$	(0.0639)	(0.1043)	(0.0892)	(0.0956)	(0.0717)	(0.1034)
$food_{t-1}$	0.00388***	0.00063**	0.00253**	0.00592***	0.00315**	0.00484***
	(0.0011)	(0.0003)	(0.0012)	(0.0017)	(0.0014)	(0.0018)
$food_{t-2}$	0.00268***	-0.00011	0.00197**	0.00312**	0.00088	0.00333***
	(0.0009)	(0.0001)	(0.0008)	(0.0013)	(0.0009)	(0.0008)
$food_{t-3}$	0.00170*	-0.00026	0.00169*	0.00307**	0.00170*	0.00144
	(0.0009)	(0.0002)	(0.0009)	(0.0013)	(0.0009)	(0.0009)
1st Stage F-stat	139.87	24.04	135.53	248.03	238.44	33.82
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	9950	10950	3913	12399	8519	7790
R^2	0.949	0.851	0.969	0.937	0.949	0.969

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 for each column are derived as discussed in Section 2.5. 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. 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. The full set of coworkers' hens' age dummies is used in the first stage in all columns. $food_{t-s}$ are lags of amount of food distributed as measured by 50kg sacks employed.

Table B.4: Incentives Heterogeneity: Estimation across Subsamples



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.1: Distribution of Estimated Worker Fixed Effects

B.3 Termination Policy and Observable Input Quality

In this section, we further extend the conceptual framework in Mas and Moretti [37] 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

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

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

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

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

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

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

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

Taking logs we get

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

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

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

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

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

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 B.3 and Figure B.3 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

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

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

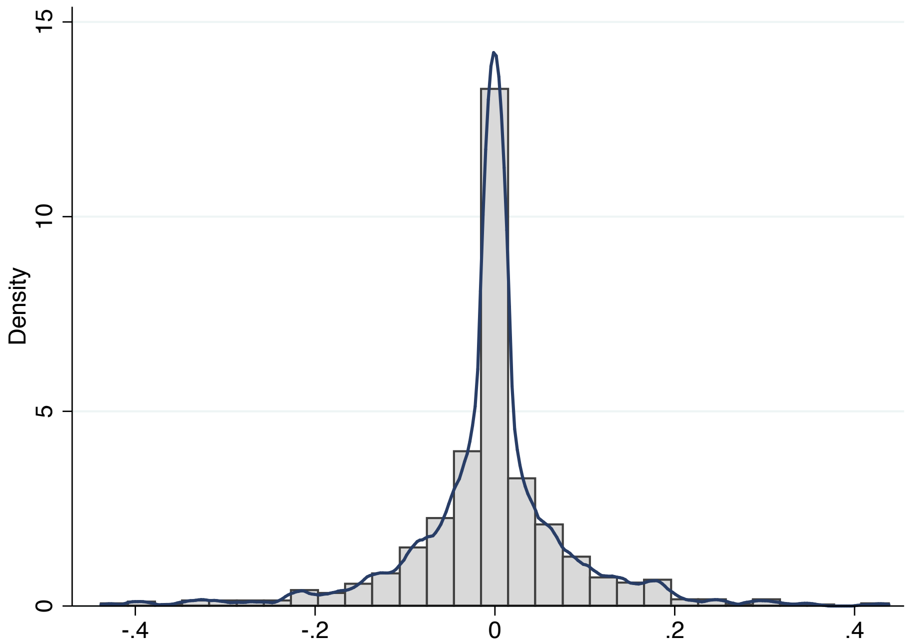
Notice that, since $b < 1$, the probability of keeping the job increases with both the individual signal v_i and any coworkers' signal v_{-i}. Furthermore, consistently with the empirical analysis, it can be shown that, given the expected idiosyncratic random shock $\mathbb{E}(\eta_i) = \frac{1}{2}$,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

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 2.3 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 B.

Table B.5: Simulated Distributions



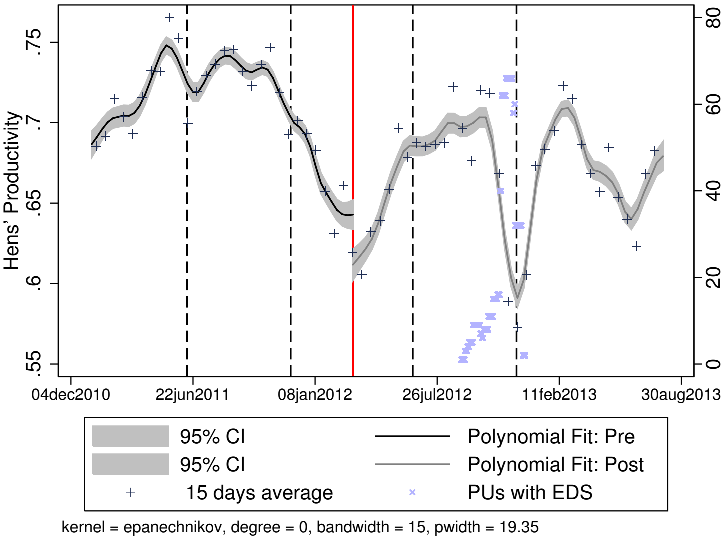
Notes. The figure plots the distribution of $\phi(\eta_i, a_i)$ as derived from the values of η_i, a_i and $g(a_i)$ reported in Table B.3, together its the smoothed kernel density.

Figure B.2: Simulated Distribution of $\phi(\eta_i, a_i)$

Appendix C

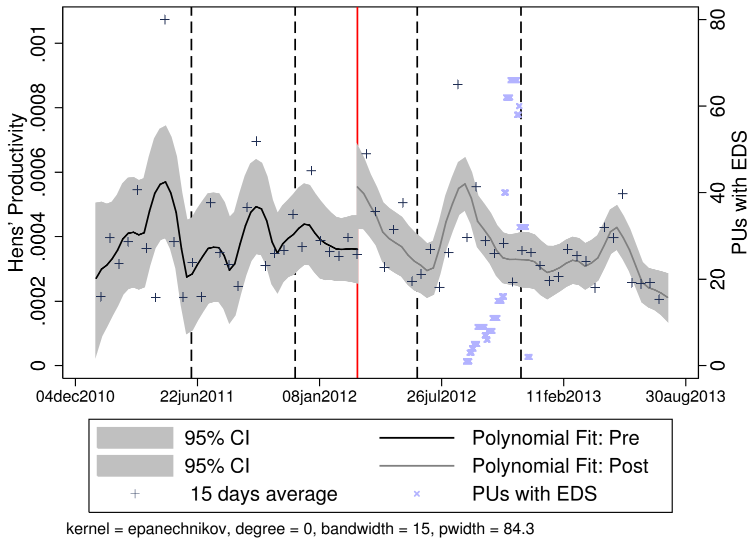
APPENDIX: CHAPTER 3

C.1 Evolution of secondary variables over time



Notes. This graph plots the kernel-weighted local polynomial approximation to the number of good/total number of eggs by production unit from January 2011 to July 2013. The graph shows the smoothed average together with its 95% confidence interval dividing the sample in the two periods characterize by the different contractual structures. The vertical red lines separate the years and the vertical black line indicates the first fortnight after the change in the incentive scheme.

Figure C.1: Percentage of good/total number of eggs over time



Notes. This graph plots the kernel-weighted local polynomial approximation to the number of casualties/total number of hens by production unit from January 2011 to July 2013. The graph shows the smoothed average together with its 95% confidence interval dividing the sample in the two periods characterize by the different contractual structures. The vertical red lines separate the years and the vertical black line indicates the first fortnight after the change in the incentive scheme.

Figure C.2: Percentage of casualties/total number of hens over time

C.2 Estimated Parameters: Regressions

Variable	**Est. Coef.**	**St. Error**	**95% Conf. Int.**	
without controls:				
$\hat{\theta}$	8.4479	0.3668	7.5882	9.0265
$tan(\hat{\theta})$	0.1485	0.0074	0.1348	0.1679
$\frac{E[\hat{Q}_2^I]}{E[\hat{Q}_1^I]} - \frac{E[\hat{Q}_2^{II}]}{E[\hat{Q}_1^{II}]}$	0.0106	0.0010	0.0086	0.0122
controlling by number of hens:				
$\hat{\theta}$	8.4479	0.3549	7.6858	9.0640
$tan(\hat{\theta})$	0.1485	0.0066	0.1374	0.1606
$\frac{E[\hat{Q}_2^I]}{E[\hat{Q}_1^I]} - \frac{E[\hat{Q}_2^{II}]}{E[\hat{Q}_1^{II}]}$	0.0106	0.0010	0.0086	0.0125
all controls:				
$\hat{\theta}$	8.4479	0.3907	7.61949	9.1418
$tan(\hat{\theta})$	0.1485	0.0072	0.1304	0.1605
$\frac{E[\hat{Q}_2^I]}{E[\hat{Q}_1^I]} - \frac{E[\hat{Q}_2^{II}]}{E[\hat{Q}_1^{II}]}$	0.0106	0.0010	0.0088	0.0129

Notes. The Table reports the estimated parameters depending on the estimated means of the observed performance measures by type of contract. The means are estimated using seemingly unrelated regressions and predicting expected value of the measures at the mean of the control variables when it is the case. We obtain the standard errors and confidence intervals using bootstrapping with replacement, 100 repetitions in total.

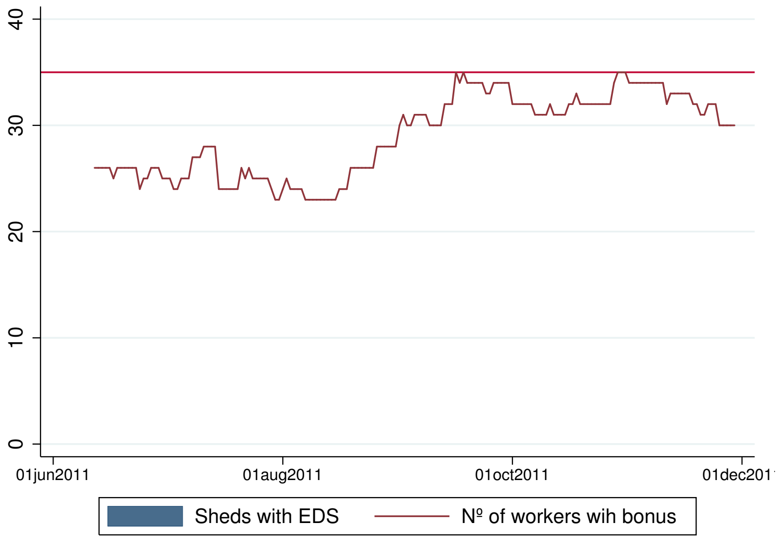
Table C.1: Distortion among performance measures

	Egg's Boxes			
	(1)	(2)	(3)	(4)
Food (50Kg Sacks)	0.432***	0.414***	0.395***	0.414***
	(0.017)	(0.031)	(0.09)	(0.09)
No of hens	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.00)	(0.00)
Age	0.097***	0.041***	-0.029	0.014
	(0.006)	(0.007)	(0.04)	(0.04)
Age^2	-0.002***	-0.001***	-0.001	-0.001**
	(0.000)	(0.000)	(0.00)	(0.00)
Daily Temperature	-0.103***	-0.066***	-0.022	-0.056*
	(0.009)	(0.007)	(0.03)	(0.03)
Daily Humidity	0.011 ***	0.009***	0.009	0.007
	(0.003)	(0.003)	(0.01)	(0.01)
Sheds wiht EDS	-0.053***	-0.057***	-0.048***	-0.056***
	(0.001)	(0.002)	(0.01)	(0.01)
Contractual Change	0.194***			
	(0.030)			
Constant	-0.012			
	(1.69)			
Interactions terms	No	Yes	Yes	Yes
Worker Fe	No	Yes	Yes	Yes
Batch Fe	No	No	Yes	No
Shed Fe	No	No	No	Yes
N	17798	17798	17798	17798
R^2	0.977	0.952	0.59	0.60
$\hat{Var}(\varepsilon_{ilt})$	1.75***	1.04***	0.90	0.99
	(0.034)	(0.023)		
No of IT(+)	-	35	37	34

Notes. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Ordinary Least Square estimates. Sample is restricted to the observations belonging to the steady states periods defined on section 3.5. Moreover, we do not consider the observations of the hens on the first and thenth deciles of hens' age.

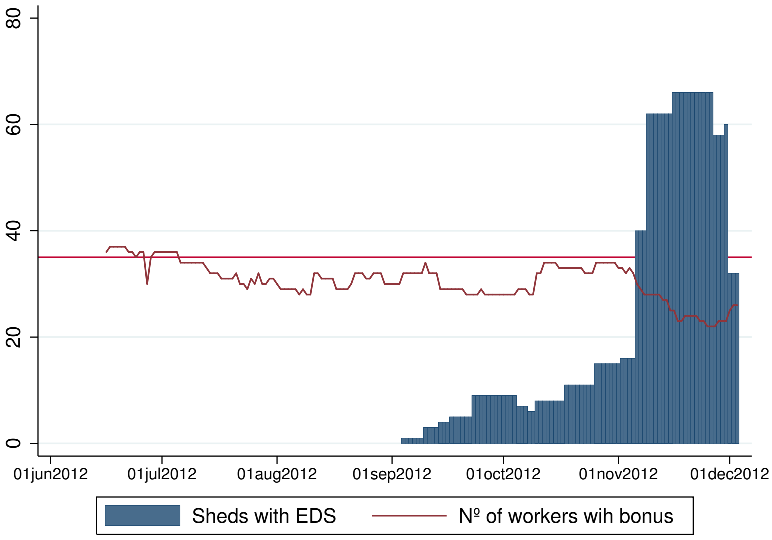
Table C.2: Estimated Coefficients

C.3 Performance measures and performance threshold



Notes. The figure plots the number of workers whose performance measures levels allow them to receive a bonus. This graph represents the period before the contractual change. We use only the observations of the workers on the steady states defined on section 4 and we do not consider the observations of hens on the first or tenth deciles of age.

Figure C.3: No of workers receiving a bonus: Pre contractual change

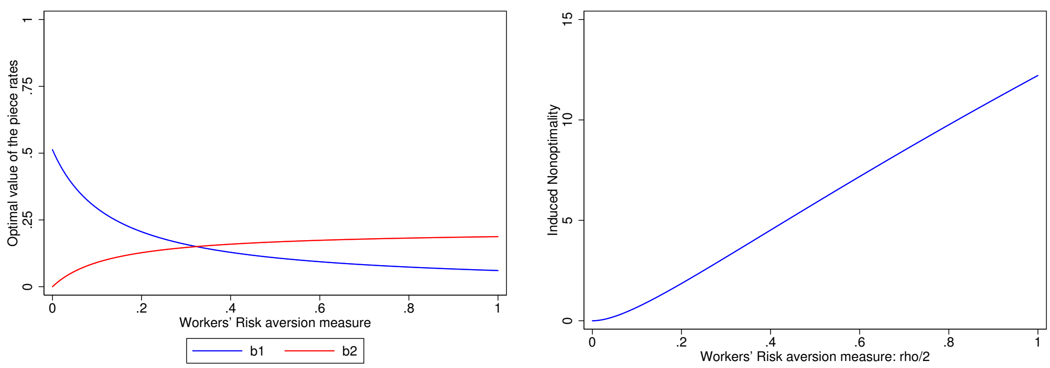


Notes. The figure plots the number of workers whose performance measures levels allow them to receive a bonus. This graph represents the period after the contractual change. We use only the observations of the workers on the steady states defined on section 4 and we do not consider the observations of hens on the first or tenth deciles of age.

Figure C.4: No of workers receiving a bonus: Post contractual change

C.4 Estimated piece rates and profits: $p_1 = 1$ and $p_2 = 0$

The optimal piece rates are plotted in left hand side panel of Figure $C.5$. When the agents are risk neutral, the variance of their payments has no impact of their utility level, the optimal contract is such that $b_1 = \tilde{T}_1/2\tilde{T}_2 \approx 0.51$ and $b_2 = 0$. On the other extreme, when the risk aversion measure of the workers tends to infinite, the optimal contract is such that $b_1 \to 0$ and $b_2 \to (T_1/2T_2)(g_{12}/g_{22}) \approx 0.21$. If the workers are risk neutral, the principal should use the perfectly aligned performance measure beyond the real worker's effort this measure is capturing. But, when the workers are risk averse, the principal has to offer them an insurance to cover them from the risk they are bearing or to increment the piece rate related to the performance measure the workers can perfectly control.



Notes. The left hand side panel plots the predicted piece rates of the optimal contract using both performance measures. The right hand side plots the induced profit losses as a consequence to discard the misaligned but noiseless performance measure on the final contract. The x-axis in both cases is the workers risk aversion parameter, $\phi = \rho/2$. The higher the value of ϕ, the more risk averse the agents.

Figure C.5: Optimal piece rates and induced profits losses: $P_1 = 1$ and $P_2 = 0$

C.5 Mathematical Appendix

Lemma 1

Proof. Notice that:

$$\tilde{T}_1 = E\left[\frac{1}{c}|c < \tilde{c}\right] = \int_{\underline{c}}^{\tilde{c}} \frac{1}{c}\frac{f(c)}{F(\tilde{c})}dc$$

where $\frac{f(c)}{F(\tilde{c})}$ is the truncated distribution of the marginal cost after quota. Applying Leibniz rule, we obtain:

$$\frac{\partial \tilde{T}_1}{\partial \tilde{c}} = \left(\frac{1}{\tilde{c}} - E\left[\frac{1}{c}|c < \tilde{c}\right]\right)\frac{f(\tilde{c})}{F(\tilde{c})}$$

Notice that $\frac{\partial \tilde{T}_1}{\partial \tilde{c}}$ is always negative since $1/\tilde{c} < E[1/c|c < \tilde{c}]$. It implies that $\varepsilon_{\tilde{T}_1,\tilde{c}} < 0$ since $\tilde{c}$ and $\tilde{T}_1$ are always positive. We follow a similar procedure for the case of $\tilde{T}_2$ and we obtain:

$$\frac{\partial \tilde{T}_2}{\partial \tilde{c}} = \frac{\partial \tilde{T}_1}{\partial \tilde{c}} + \frac{1}{2\tilde{c}^2}$$

If we define $\hat{c}$ as the level of $\tilde{c}$ such that $\frac{\partial \tilde{T}_1}{\partial \tilde{c}} = \frac{1}{2\tilde{c}^2}$, $\frac{\partial \tilde{T}_2}{\partial \tilde{c}}$ is positive if $\tilde{c} < \hat{c}$. Since $\tilde{c}$, $\tilde{T}_1$ and $\tilde{T}_2$ are positive, we know that if $\tilde{c} < \hat{c}$, then $\varepsilon_{\tilde{T}_2,\tilde{c}} \geq 0 > \varepsilon_{\tilde{T}_1,\tilde{c}}$

On the other hand, if $\tilde{c} > \hat{c}$ we know that $\frac{\partial \tilde{T}_1}{\partial \tilde{c}} < \frac{\partial \tilde{T}_2}{\partial \tilde{c}} < 0$, which implies:

$$\frac{\partial \tilde{T}_1}{\partial \tilde{c}} > -\frac{1}{2\tilde{c}^2}$$

We also know that $\tilde{T}_1 > \tilde{T}_2$ and $1/\tilde{T}_1 > 1/\tilde{T}_2$. Then, we need to evaluate if $varepsilon_{\tilde{T}_1,\tilde{c}} - \varepsilon_{\tilde{T}_2,\tilde{c}} < 0$ when $\tilde{c} > \hat{c}$. If $varepsilon_{\tilde{T}_2,\tilde{c}} < 0$, we have:

$$\frac{\tilde{c}}{\tilde{T}_1}\frac{\partial \tilde{T}_1}{\partial \tilde{c}} < \frac{\tilde{c}}{\tilde{T}_2}\frac{\partial \tilde{T}_2}{\partial \tilde{c}}$$

Replacing $\tilde{T}_2$ and $\frac{\partial \tilde{T}_2}{\partial \tilde{c}}$, we get:

$$\frac{\tilde{c}}{\tilde{T}_1}\frac{\partial \tilde{T}_1}{\partial \tilde{c}} < \frac{\tilde{c}}{\tilde{T}_1 - (1/\tilde{c})}\left(\frac{\partial \tilde{T}_1}{\partial \tilde{c}} + \frac{1}{2\tilde{c}^2}\right)$$

After some calculation, it implies that:

$$\frac{\partial \tilde{T}_1}{\partial \tilde{c}} > -\frac{\tilde{T}_1}{2\tilde{c}}$$

Finally, we can show that if $\tilde{c} > \hat{c}$, then $\varepsilon_{\tilde{T}_1,\tilde{c}} - \varepsilon_{\tilde{T}_2,\tilde{c}} < 0$. It is because:

$$\frac{\partial \tilde{T}_1}{\partial \tilde{c}} > -\frac{1}{2\tilde{c}^2} > -\frac{\tilde{T}_1}{2\tilde{c}}$$

The last inequality is true since $\tilde{T}_1 > 1/\tilde{c}$ is always the case.

□

Proposition 1

Proposition 3. *Given a constant k, when we have two performance measures, Q_1, Q_2, and two contracts assigning them a piece rate value, $b^I = (b_1^I, b_2^I)$ and $b^{II} = (b_1^{II}, b_2^{II})$,*

1. *When there are more than two tasks, if measures are perfectly aligned then $\frac{E[Q_2^{II}]}{E[Q_1^{II}]} = \frac{E[Q_2^I]}{E[Q_1^I]} = k$, but $\frac{E[Q_2^{II}]}{E[Q_1^{II}]} = \frac{E[Q_2^I]}{E[Q_1^I]} = k$ if $(\sum_j g_{1j})(\sum_j g_{2j}) = (\sum_j g_{1j}g_{2j})^2$.*
2. *When we have only two actions, $\frac{E[Q_2^{II}]}{E[Q_1^{II}]} = \frac{E[Q_2^I]}{E[Q_1^I]} = k$ if and only if measures are perfectly aligned.*

Proof. In the general case, the expected value of the performance measures available are:

$$E[P_k] = (\sum_i b_i(\sum_j g_k j g_i j))E(1/c|c < \tilde{c})$$

When we have two performance measures, P_2 and P_1, the ratio of their expected values is:

$$\frac{E[P_2]}{E[P_1]} = \frac{(\sum_j g_{2j}g_{1j}) + R(\sum_j g_{2j}^2))}{(\sum_j g_{1j}^2) + R(\sum_j g_{1j}g_{2j}))}$$

where $R = \frac{b_2}{b_1}$.

If the performance measures are perfectly aligned, $g_{2j} = kg_{2j}$, where k is a constant. If we replace g_{2j} in the previous expression, we have:

$$\frac{E[P_2]}{E[P_1]} = \frac{k(\sum_j g_{1j}^2) + Rk^2(\sum_j g_{1j}^2))}{(\sum_j g_{1j}^2) + Rk(\sum_j g_{1j}^2))} = k$$

independently of the value of R.

On the other hand, if we have two different contracts R^I and R^{II}, we have that:

$$\frac{(\sum_j g_{2j}g_{1j}) + R^I(\sum_j g_{2j}^2))}{(\sum_j g_{1j}^2) + R^I(\sum_j g_{1j}g_{2j}))} = \frac{(\sum_j g_{2j}g_{1j}) + R^{II}(\sum_j g_{2j}^2))}{(\sum_j g_{1j}^2) + R^{II}(\sum_j g_{1j}g_{2j}))}$$

$$R^I\left[(\sum_j g_{2j}g_{1j})^2-(\sum_j g_{1j}^2)(\sum_j g_{2j}^2)\right]=R^{II}\left[(\sum_j g_{2j}g_{1j})^2-(\sum_j g_{1j}^2)(\sum_j g_{2j}^2)\right]$$

where, they are equal if $(\sum_j g_{2j}g_{1j})^2-(\sum_j g_{1j}^2)(\sum_j g_{2j}^2)=0$, which is satisfied if the measures are perfectly aligned but it is not the only case.

In particular, when we have just two actions, the previous expression becomes $(g_{11}^2+g_{12}^2)(g_{21}^2+g_{22}^2)>(g_{11}g_{21}+g_{12}g_{22})^2$. After some calculation we can show that the previous equation reduces to $\frac{g_{11}}{g_{12}}=\frac{g_{21}}{g_{22}}$. In other words, only when the measures are perfectly aligned. □

Proposition 2

Proof. Given the definitions of z_1 and z_3 and dot product, we know that $z_1z_3=(cos\theta)^2$. Then,

$$\theta=cos^-1\sqrt{z_1z_3}$$

Moreover, we know that:

$$\frac{E[P_2]}{E[P_1]}=\frac{z_1+Rz_2}{Rz_1+1}$$

Since we observe two different contracts $R^I=b_2^I/b_1^I$ and $R^{II}=b_2^{II}/b_1^{II}$:

$$\frac{E[P_2^I]}{E[P_1^I]}=X^I=\frac{z_1+R^Iz_2}{R^Iz_1+1}$$

$$\frac{E[P_2^{II}]}{E[P_1^{II}]}=X^{II}=\frac{z_1+R^{II}z_2}{R^{II}z_1+1}$$

From the first equation, we can easily get:

$$z_2=\frac{(X^I)(R^Iz_1+1)-z_1}{R^I}$$

Replacing this expression on X^{II} and solving for z_1, we get:

$$z_1=\frac{X^{II}R^I-R^{II}(X^I)}{(R^I-R^{II})+R^IR^{II}(X^I-X^{II})}$$

Remember that by definition, $z_3=z_1/z_2$.

□