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Heterogeneous agents and decison making within firms

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Chapter 1

Introduction

Chapter 1: Introduction

1.1. Background

A central concern within this dissertation is the firm's internal decision making, particularly in the situation where information relevant to decision making is not contractible. This dissertation focuses on the role of individual heterogeneity in the internal decision making. The primary interest of previous accounting studies is in information quality, such as the quality of performance signals in compensation design. However, information quality is determined by the demand and supply, which are associated with decision makers and information providers, respectively. Those individuals may have their own preferences related to their personal characteristics or their personal relationships with other individuals. This dissertation aims to extend the focus of the information quality by considering the effects of personal characteristics or relations between employees on information use or supply.

The traditional agency model relies on *ex ante* incentives to solve moral hazard problems. The model of Hölmstrom (1979) offers two insights on the design of incentive contracts: (1) risk sharing between principal and agents, and (2) informativeness of performance signals. The Hölmstrom model only incorporates individual preferences for risk, and largely sidesteps the possibility of agent heterogeneity. Empirical evidence associated with the second insight finds that organizational design (e.g.delegation), complicates the choices of performance signals (Abernethy et al. 2004; Bouwens and Van Lent 2007; Moers 2006). More importantly, it is not easy to find appropriate performance signals, and personal *ex post* discretion plays a role (Baker et al. 1994; Prendergast and Topel 1993); this situation makes individual heterogeneity salient.

There is an increasing amount of evidence that individuals differ from each other on multiple dimensions. For example, Ichino and Maggi (2000) find that a given individual's background affects the level of effort. Others show that selecting employees whose preferences are in line with those of the firm can help to mitigate control problems (e.g., Campbell 2012). In all but the most simple environments, employees work with each other and thus in addition to these employees' own characteristics, interpersonal relations also play a role in the work place (Mas and Moretti 2009; Bandiera et al. 2005).

Individual heterogeneity is a factor in understanding the specifics of the internal decision making. This dissertation discusses how personal characteristics and the relations among agents affect (1) the way in which individuals use information to make decisions and (2) whether individuals are willing to share information. The following three chapters in this dissertation use data from the field to shed light on these relations.

1.2. Outline and Preview

In chapter 2,[1] I examine whether managers' ability affects the informal agreement (i.e., relational contracts) that managers maintain in their department by looking at the association between managers' ability and their discretionary decisions in allocating bonuses to themselves and to their subordinates. I characterize the relational contracts as on-going versus period-by-period contracts by the extent to which individuals (including managers and subordinates) trade off long-term gains against short-term payoff. High-ability managers are more patient and are more capable of realizing long-term gains than low-ability managers, so high-ability (low-ability) is associated with on-going (period-by-period) relational contracts. Managers' bonus decisions are a manifestation of the type of relational contracts in force. I consider two (related) decisions: (1) the portion of the bonus pool that managers keep for themselves and (2) the degree to which managers differentiate the bonuses they allocate to

[1] This paper is joint work with Margaret Abernethy and Laurence van Lent.

their subordinates. I predict that managers' ability is negatively associated with (1) the proportion of the bonus pool that managers keep for themselves, and (2) the degree to which department heads differentiate the bonuses they allocate to their subordinates. Using a proprietary dataset from a Chinese hospital, we find evidence consistent with the predictions on the two types of bonus decisions.

In chapter 3,[2] I examine the effects of workforce homogeneity on effort provision and learning outcomes using a proprietary dataset from a Chinese manufacturing plant. We obtain data on the background of the employees (i.e., their hometown) and on how employees entered the firm (using the recruitment channel of referral by current workers or not). We argue that workers from the same hometown and referred workers will have lower communication and coordination costs when working together. Based on these arguments, we measure workforce homogeneity with the degree of hometown homogeneity and the proportion of referred workers. We exploit differences in the production layout of the manufacturing plant to examine how the effect of workforce homogeneity varies across two types of production environments: (1) team-based production with group incentives and (2) individual work stations in a manufacturing line along with individual incentives. Our results show that workforce homogeneity influences employee learning, but its effect depends on the specific production environment along with incentive contracts. However, we do not find evidence on the effect of workforce homogeneity on effort provision.

In chapter 4, I investigate the role of working relations between decision makers and information providers, specifically how the working relation affects both decision making and information reporting. I use a dataset of used-car loan applications from a car dealership in Taiwan where the working relation is shaped by the organizational structures (i.e., franchisees or company-owned outlets). Loan applications are submitted via either

[2] This chapter is co-authored with Laurence van Lent and Anne Wu.

franchisees or company-owned outlets. The loan rate is the communication device through which salespeople influence loan officers' approval decisions. I argue that loan officers are more uncertain about information reporting quality from franchisees than owned outlets', and expect that reporting uncertainty gives rise to both loan officers' decision biases and salespeople's reporting biases. Consistent with the decision bias hypothesis, I find that loan officers, in response to an increase in the loan rate, are more likely to reject franchisees' applications than owned outlets'. Also, franchisees set a lower loan rate but have a higher default rate than owned outlets. This finding supports the reporting biases hypothesis that salespeople (especially those in franchisees) skew loan rates downward to offset loan officers' decision biases.

In sum, the three chapters broaden the focus of previous work on the role of information quality in internal decision making by emphasizing the effects of personal characteristics or relations between employees on information use and information supply.

1.3. Conclusion

Firms *ex ante* design a mechanism to induce agents' optimal efforts or truth telling. This view of mechanism design implies that what we *ex post* observe in the real world is the optimal outcome of the designed mechanism. What my dissertation adds to this framework is to demonstrate that inputs (e.g., employees) of this mechanism matters; agent heterogeneity is more than a random noise left by the "optimal" mechanism design. Agents are not exogenously determined but endogenously chosen by the firm. Hence, my dissertation broadly speaks to the match between employees and internal control system. This idea has received attention by economists (Lazear 2000), and recently gets more attention in finance (Carlin and Gervais 2009) and accounting (Hales et al. 2014).

In addition, given that there are many contingencies that firms cannot contract on *ex ante*, firms might apply other means to complement or replace incentive contracts. For example, Hertzberg et al. (2010) find that an Argentina bank applies employee rotation to mitigate the misreporting about borrowers' credit risk, which is not verifiable. However, accounting research doesn't address much about implications of personnel practice, such as hiring, for incentives contracts (Oyer and Schaefer 2011).

It will be a long journey to understand the role of personnel practices in the internal control system. I only consider my dissertation as a step in recognizing the role of agent heterogeneity in addition to risk sharing and informativeness of performance signals in traditional agency models. A next equally important question that needs to be addressed next is how the match between agents and firms characteristics is achieved and whether firms apply other control systems to solve or avoid any mismatch between the agent and the firm.

Empirical research is designed to validate established theory (or to explore avenues for theory building). Each theory has different sets of assumptions. Reflecting on the past research development, there are many theoretical advances which lack supporting empirical evidence. The challenge of empirical work is the access to the right data, which meets the set of assumptions in the theory (Bartel et al. 2004). Survey is a common approach to collect data on decision making within firms, but surveyed data only accounts for general heterogeneity across or within firms with limited specifics of the firms. In addition, it is not clear whether the responses are free of any personal biases. As the rich and detailed background information of field work allows for a careful assessment of the fit between data and the assumption of the theory, I apply field studies in an attempt to narrow the gap between theory and empirical research.

Ichniowski and Shaw (2003) label the approach of field empirical work "insider econometrics". The obvious drawback of this approach is that one is less able to assess the generalizability of the results. However, field empirical work offers the greater confidence on accuracy of interpretation of empirical results, which is weighted against the drawback.

Given the fact that theoretical advancement goes beyond empirical research, I believe that the merit of field work outweighs the drawback.

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Chapter 2

Managerial Ability and Discretionary Bonus Decisions

Chapter 2: Managerial Ability and Discretionary Bonus Decisions[3]

2.1. Introduction

Individual preferences and ability are 'fundamental determinants of decision making in economic models' (Dohmen et al. 2010). The effect of ability on decision making has received little attention in the accounting literature despite its relevance for employee sorting and contract design. We argue that a key determinant of the different choices that managers make when allocating bonuses is ability.[4] We test this relation in a setting where subordinates' actions can neither be specified *ex ante* nor *ex post* verified. In other words, managers must rely on a relational contract, which is defined as informal agreements and unwritten codes of conduct, to influence the behaviors of individuals within firms (Baker et al. 2002). We make a direct link between relational contracts and a manager's discretionary bonus choices. We investigate the association between managers' ability and their relational contracts with subordinates by examining their discretionary bonus decisions.

We borrow insights from Gibbons and Henderson's (2012) description of relational contracts and identify two types of relational contracts; one is the ongoing contract (i.e., the repeated game) where employees maximize long-term payoff by cooperating with each other; the other is the period-by-period contract (i.e., the one-shot game) where employees maximize short-term gains by taking opportunistic actions. We recognize that a manager faces multiple choices when implementing a relational contract. However, bonus decisions reflect an important component of a relational contract given their influential role in shaping employees' behaviors (Roberts 2010). When managers are granted the authority to allocate

[3] This chapter is co-authored with Margaret Abernethy and Laurence van Lent.
[4] We assume that ability is a characteristic that cannot be mimicked either because it is too costly or infeasible to do so for any period of time.

bonuses, we argue that the bonus decision allows them to communicate to their subordinates their preferences for the type of relational contracts they want with their subordinates.

We choose a rich and somewhat unique setting in which to study the role of ability in discretionary bonus decisions. Ability is particularly salient in professionally dominated organizations such as hospitals, law and accounting firms and among academics working in universities. Our research site is a large hospital that has multiple clinical departments with physicians as heads of departments and a group bonus system based on department performance. All clinical heads have formal authority but differ in their ability both in relation to other clinical heads and to other clinicians working in their departments. They have almost complete discretion to determine how the group bonus is distributed within their department. There is a fixed bonus pool for each department based on the department's prior performance. Managers can decide on (1) how much they can keep to themselves, and (2) how they distribute the remaining bonus to subordinates. While it is not common for a manager to decide on how much bonus they keep for themselves, it is this specific feature that allows us to test whether managers' ability affect choices in the implementation of relational contracts. This feature also helps us to overcome the empirical difficulty of measuring unobserved relational contracts. Therefore, we present evidence on the association between managers' ability and two choices managers make when allocating bonuses.

The work performed in clinical units also provides a relevant context within which to examine relational contracts, namely, it is difficult both to specify *ex ante* desired actions and measure *ex post* with any degree of accuracy. Professional judgment and expertise is assumed to be critical in this context (Freidson 1970; Scott 1982); it is also recognized that professionals, such as physicians, invest heavily in their own human capital (Pizzini 2010).

We argue that high-ability managers are better able to implement ongoing relational contracts for two reasons. First, based on prior research, we expect that high-ability managers are more able to make the right decisions as they have higher levels of knowledge, expertise and judgment to guide the actions of their subordinates (Demerjian et al. 2012). Second, high-ability managers have the ‘patience’ to engage in a long run game. They recognize the long term gains of creating a collaborative work environment where employees cooperate rather than compete. Prior empirical research demonstrates that ability varies systematically with ‘patience’ (Dohmen et al. 2010). Gibbons and Henderson argue that patience is important when choosing the type of relational contract. Managers with patience will prefer to implement ongoing relational contracts that have long term payoffs; in other words they have the ‘patience’ to wait for the benefits associated with those long term payoffs. Given the association between ability and patience, we expect that high-ability managers are more willing to implement ongoing relational contracts than low-ability managers. In sum, we expect that high-ability managers are both more capable of identifying the right course of action for the long run success and have the patience to implement contracts that have long term payoffs. Low-ability managers only have the option of period-by-period relational contract due to constraints in their ability.

We link the choice of relational contract to bonus decisions by drawing on Gibbons and Henderson’s (2012) description of the Trust game. The bonus decision can be seen as one manifestation of the relational contract; it provides a means of communicating the manager’s contract preference. We predict that managers who choose an ongoing relational contract will communicate their preferences as follows. First, they will keep a smaller share of the bonus pool for themselves (i.e., leave more bonuses to subordinates). Keeping a smaller share of the bonus shows the manager’s willingness to sacrifice short-term payoff for long-term gains. Second, they will distribute the remaining bonus to subordinates more evenly, that is, there will be less differentiation among the bonuses provided to subordinates. The even distribution of bonus among subordinates encourages cooperation as opposed to competition. We expect high-ability managers to recognize the long term benefits of maintaining a repeated relationship, and that low-ability managers are constrained to a one-shot relationship. While high and low ability managers manage their organizations with different preference for time horizons (i.e. long-term versus short-term), we would expect in this setting that choices that encourage collaboration and cooperation among employees would on average have better longer term outcomes (e.g. better patient care, increased reputation of the hospital, etc.) than bonus decisions that increase competition and opportunism.

Our empirical findings are consistent with our predictions. We find that high-ability managers keep a smaller share of bonus than low-ability managers, and high-ability managers distribute bonus to employees more evenly than low-ability managers. We interpret these findings as evidence that managers' ability is associated with the extent to which they are capable of building an ongoing relational contract within the department.

We recognize, however, that the bonus decision is only one manifestation of the choices that a manager makes in the implementation of relational contracts. We also recognize that ability is most likely to be highly correlated with power and reputation. Prior research examines the influence of managerial power and/or reputation as determinants of economic decisions within the firm, so there are possibly alternative theoretical explanations for our observed relation between ability and bonus decisions. We elaborate further on alternative explanations in relation to our findings in Section 2.4.3 of the paper.

This study contributes to prior research in a number of ways. By assessing the choices managers make in determining discretionary bonuses, we are able to shed some light on the question of how relational contracts can be implemented within a firm. We also contribute to the growing body of research examining how managerial traits influence the economic decisions managers make within the firm (Malmendier and Tate 2009; Jia et al. 2014;

Malmendier and Tate 2005).[5] And finally we contribute to research examining the determinants of subjectivity in performance measurement and compensation decisions. Only a few empirical studies directly investigate determinants of discretion in bonus decisions (Gibbs et al. 2004; Rajan and Reichelstein 2006; Bol 2011; Ederhof 2010). Our findings indicate that managers' ability is an important personal characteristic determining the way they manage their departments. While ability might be correlated with other personal traits (e.g., overconfidence), what sets ability apart is that it is difficult to mimic; there are clear markers of ability and thus empirically it is possible to identify differences among managers.

We also study two types of compensation decisions. Prior studies either discuss how managers reward themselves (i.e., seek rents) or how managers reward their subordinates. Using a setting where relational contracts are likely to exist, we are able to offer a more holistic view of the decisions managers make when allocating bonuses.

2.2. Hypothesis Development

2.2.1. Relational Contracts

Firms have formal decision rights, procedures and rules in place to govern organizations, but informal rules and expectations also powerfully affect the behaviors of individuals within firms (Hermalin 2013). Baker et al. (2002) term the informal agreements and unwritten codes of conduct as "relational contracts".[6] The classic example of relational contracts is the Toyota production system, under which line workers are asked to become "active problem solvers". However, management cannot define in advance exactly which problems line workers might find or how problems should be solved. Another example is Lincoln Electric's "fair" principle in bonus payment practice, but there is no manual to define exactly what constitutes a fair bonus for a particular worker in a particular year. Those

[5] Prior literature uses physical traits or past experience (e.g., military services or religion) to measure managers' personal traits (e.g., overconfidence, integrity, or dominance) and documents the effect of these different characteristics on corporate investment, financial reporting decisions and tax policies.

[6] The idea of informal agreements is close to what Hermalin (2013) describes as corporate culture or leadership.

employees take the actions based on their understanding of what is expected or acceptable within the given firm, namely the relational contracts.

There are many variations in the forms that relational contracts can take. In our research setting, the high degree of discretion in bonus allocation makes the research setting resemble the set-up of the Trust game described by Gibbons and Henderson (2012). We thus rely on their description of the Trust game to understand how bonus decisions reflect the nature of relational contracts. The trust game works as follows. Managers take the initiative and play a strategy of either “Trust” or “Distrust”; employees could respond to managers’ Trust by playing either “Honor” or “Betray”. However, if managers play Distrust, the game ends. The manager’s strategy depends on her anticipation of employees’ responses. This anticipation exactly captures the spirit of a relational contract, namely the informal agreement and the unwritten codes of conduct. If managers anticipate that employees will respond with “Betray”, they will play “Distrust” as an initial move. If managers anticipate employees’ response to be “Honor”, they will play “Trust”. The different anticipations result in two types of games: repeated game and one-shot game. In the repeated game, managers play Trust and employees respond with Honor; in the one-shot game, managers play Distrust and the employees end the game.

We borrow insights from the Trust game to characterize the relational contracts. In a repeated game, individuals (managers and employees) view their collaboration as an ongoing relationship; thus they care about the consequences of their actions today on the future. On the contrary, in a one-shot game, individuals assume that their relationship will end at any random point of time, so they limit their attention to actions that affect the current period. For exposition purpose, we identify two discrete types of relational contracts: an ongoing relational contract (i.e., a repeated game) and a period-by-period relational contract (i.e., a one-shot game). Under an ongoing relational contract, individuals work cooperatively to maximize payoff *over time*. A period-by-period relational contract is a short-term contract where individuals maximize their payoff *today* by taking opportunistic behaviors. We recognize, however, the choice of relational contracts is not binary, but a continuum in terms of the extent to which the value of long-term relationship outweighs the short-run temptation of opportunistic behaviors.

2.2.2. Managerial Ability and Relational Contracts

Given the different types of relational contracts, the relevant question is why they vary. As opposed to formal contracts enforced by courts, relational contracts are subject to individual influence, so managers' characteristics play a role in establishing the relational contracts. We treat managers' choice of relational contracts as an economic decision. Ability is the characteristic that differentiates managers' cost function of managing their organizations. Some management practices are simply too costly or even infeasible for low-ability managers. The difference in their cost function clearly predicts a separating equilibrium where high-ability managers choose different relational contracts from low-ability managers. We argue that high-ability managers will choose ongoing relational contracts, but low-ability managers will choose period-by-period (i.e., one-shot) relational contracts.

The key distinction between ongoing and period-by-period relational contracts is the extent to which individuals trade off long-term gains against short-term payoff. As opposed to low-ability managers, high-ability managers have sufficient knowledge to identify the right course of action for long-run success. At the same time, high-ability managers have the expertise that allows them to coordinate subordinates' actions through appropriate task assignment and timely settlement of any conflicts occurring *ex post*. Not only are high-ability managers better at decision making and task execution (Demerjian et al. 2012) they are more patient. Empirical research demonstrates that 'patience' and ability co-vary. Patience is critical for ongoing relational contracts (Gibbons and Henderson 2012). The patience of high-ability managers allows them to wait for gains that accrue over the longer term. In other words, high-ability managers will choose to establish ongoing relational contracts because they are able to both generate long-term payoff and can wait patiently to realize the long-term payoff.

Conversely, low-ability managers are constrained by their lack of knowledge, experience, or expertise. They do not have the ability to develop a viable long-term action plan or to coordinate subordinates to implement the action plan. In other words, it is less likely for low-ability managers to realize high long-term payoff than for high-ability managers. In addition, low-ability managers are less patient, so they value the current payoff more than long-term benefits. Therefore, low-ability managers will choose period-by-period relational contracts because of the limitation of their ability.

In sum, we expect that managers' ability affects their choice of relational contracts; high-ability managers will choose ongoing relational contracts, but low-ability managers will choose period-by-period relational contracts where the payoffs are immediate.

2.2.3. Managerial Ability and Discretionary Bonus Decisions

Relational contracts rely on employees' following the signals or actions of their superior (Hermalin 1998). In that sense, managers will need to communicate, or provide a signal, to their employees as to their preferred type of relational contract and ensure that the relational contract chosen is implemented (Hermalin 1998). We know that the choice of incentive contract influences employees' behavior (Carlin and Gervais 2009). When managers have discretion in the allocation of bonuses, this discretion allows managers to signal to their subordinates what is expected. Therefore, we investigate managers' choices of relational contracts by looking at their discretionary bonus decisions. We discuss how two types of discretionary bonus decisions reflect managers' choice of relational contracts, separately.

When managers have discretion to reward themselves, they can show whether they are willing to sacrifice short-term payoff for long-term payoff by deciding how much bonus they keep to themselves. If the manager takes a lower share of the bonus pool then she is signaling that she prefers actions that have long run benefits over actions that have short-term benefits. She signals that she wants a long-term relationship with the subordinates. There is the added benefit that subordinates receive a larger share of the bonus pool which would reinforce the importance of directing effort to long-term actions. Given that high-ability managers are more patient, we predict that high-ability managers are more likely to sacrifice short-term benefits for long-term benefits than low-ability managers and this will be reflected in the decision of keeping less bonus to themselves. Our prediction relating to the association beween managers' ability and their decisions in allocating bonuses to themselves is summarized as follows:

> **H1:** *Ceteris paribus*, managerial ability is negatively associated with the share of bonus that managers keep for themselves.

When managers have discretion to distribute bonus among their subordinates, the differentials in bonus allocation communicates preferences for competition or cooperation (Main et al. 1993; Lazear 1989). Given the fixed bonus pool, bonus allocation is a zero sum game. Giving one individual more reduces the other's bonus. Therefore, large bonus differentials create tournament incentives which foster competition among employees rather than cooperation (Main et al. 1993). Managers use the decision on bonus differentials to show the extent to which they encourage cooperation or competition.

The realization of long-term payoff depends on the cooperation among employees. Competition might encourage individual effort (Lazear and Rosen 1981), but it also encourages uncooperative behaviors or sabotage among employees (Harbring and Irlenbusch 2011; Lazear 1989). While high-ability managers have the expertise to develop action plans for the long-term success, they also need to create an environment that encourages collaboration and cooperation among subordinates. They will create this environment through their bonus allocation decision. It follows that high-ability managers' preference for cooperation over competition will result in lower differentials in the bonus allocation to subordinates.

> **H2:** *Ceteris paribus*, managerial ability is negatively associated with the degree of bonus differentials among employees.

2.2.4. Performance Implications

This study focuses on how managers' ability affects their choice of relational contract by looking at their discretionary bonus decisions. It is managers' ability that determines managers' choices when managing their departments. There is evidence that managerial ability is related to performance on a number of dimensions (Demerjian et al. 2012). We predict that high-ability and low-ability managers choose different relational contracts to maximize their own long-term and short-term payoffs. Our arguments imply that managers maximize their utility based on different time horizons. It is thus possible that there may not be performance difference between high- and low- ability managers in any given time period, respectively. However, in the Trust game, the total payoff of managers and employees in the repeated game is higher than that in the one-shot game; that is, ongoing relational contracts result in larger welfare gains for the firm than period-by-period relational contracts.

Under an ongoing relational contract, cooperative collaboration is sustained by the 'shadow of the future' (Gibbons and Henderson 2012). Specifically, individuals take actions by considering the consequence of their actions on their future payoff. If a manager seek rents or exploit employees or employees exploit other employees, the ongoing relational contract will break down. Therefore, it is less likely for managers and employees to take opportunistic behaviors under an ongoing relational contract, which directly translates into lower agency costs. Under a period-by-period contract, individuals maximize their payoff in the current period and pay less attention to the implication for the future. In that sense, it is more likely that people seek private benefits at the expense of the department. Hence, period-by-period relational contracts imply more opportunism and result in higher agency costs.

In sum, we predict that ability (along with their chosen relational contracts) is positively associated with departmental performance. However, it is not easy to document the hospital's performance, which includes not only financial performance but also quality of medical services (e.g., patient outcomes and hospital reputation), some of which can only be easily measured in the short term. Due to the complexity of the hospital performance and data limitations, we only present limited empirical evidence on financial performance without a formal statement of hypothesis.

2.3. Research Design

In this section, we first describe the research site, including the design of the incentive plan. Next, we describe the sample and the data used to test our hypotheses. We then explain how we measure the variables of interest. We also present descriptive statistics.

2.3.1. Research Site

We require a research setting with two features: (1) managers' ability is measurable, and (2) the manager has complete discretion to make performance evaluation and compensation decisions. Our research site is a large general hospital in China, with 34 clinical departments. It has the highest rank in the classification system of Chinese hospitals,[7] and it is the only general hospital situated in a largely rural area. Each clinical department has

[7] There are nine levels in the classification system of Chinese hospitals. There are three tiers and each tier has three subsidiary levels. The classification is based on a hospital's ability to provide medical care, such as level of service provision, size, medical technology, and medical equipment.

a physician as a department head. There are three types of clinical departments: medical, surgical, and medical support.[8] The revenues for the hospital over the investigation period (i.e., 2007–2010) have grown by 1.86 times.[9] Revenues come from both outpatient (40%) and inpatient services (60%). The hospital has a profit center reporting structure in which all patient revenues are allocated to the departments as earned and all direct costs incurred where expended.

The management of clinical departments requires expert clinical knowledge and a management structure based on expertise rather than on a formal hierarchical structure. What's more, in this particular hospital, physicians do not have better outside opportunities in the region, resulting in low turnover of the medical staff. These long-term working relations further increase the salience of relational contracts at our research site. Once the informal agreements or unwritten conducucts have been established, they will have far reaching influences on employees' behaviors. Heads of clinical departments all have the same hierarchical authority but may differ in their ability.[10] We expect that the ability of clinical heads will vary across departments in our sample.

We focus only on the clinical staff, which includes both physicians and nurses. For each month, the size of the clinical staff ranges from 480 to 496 individuals. Physicians and nurses in the clinical departments receive a fixed salary as well as a bonus determined on a monthly basis. The hospital has a group bonus system in which the monthly department bonus pool is determined by the monthly department profit. There is no explicit formula for

[8] Medical departments include Pediatrics, Nephrology, Neurology and Gastroenterology. Surgical departments include Obstetrics and Gynecology, Urology, Orthopedics, Stomatology, and Neurosurgery. Medical support departments include Radiology, Ultra-sonography, and Pathology.
[9] This revenue growth is partially due to the reform of the rural cooperative medical system (RCMS). Under RCMS, the government reimburses the medical spending of listed major medical treatment for those living in rural areas.
[10] Ability as reflected in the expertise of physicians is also of value for the hospital because it is instrumental in attracting patients and thus revenue to the hospital. Patients are unable to objectively evaluate service quality and thus are attracted to hospitals with high-ability physicians.

allocating individual bonuses within the departments. The hospital does not set any individual-level performance indicators for either physicians or nurses. The general guideline is that department heads should reward a given subordinate according to his contribution to the department. However, the hospital does not document any individual-level performance data (e.g., revenue generated, number of patients treated, and quality of treatment). Nonetheless, there is one clear rule that limits the department head's bonus: it cannot be more than 3.5 times the average bonus of all subordinates within the department. Apart from this restriction, the allocation of the bonuses within the department is completely at the discretion of the department head. The department head has to make two decisions: (1) the fraction of the bonus pool she keeps for herself and (2) how much to differentiate the bonuses among subordinates in the department.[11] We study the role of ability in both these decisions.

2.3.2. Data

The hospital provided us with proprietary archival data. Data are available with respect to (1) monthly departmental performance, such as revenue, profit, and cost;[12] (2) monthly salary and bonus data at the individual level; and (3) personnel data, including age, tenure, and gender.[13] In addition to the proprietary archival data, we collect information from the hospital's website on the physicians' personal details including prizes and their memberships in medical professional associations. The hospital also identifies "star" physicians on the website. We rely on these data to measure managers' ability. Data are available from 2007 to 2010. Our data cover those formally employed by the hospital, including physicians and nurses. We have data for each nurse, physician, and head on a monthly basis grouped by department. The average department size in terms of the number of

[11] There is nothing that restricts the sharing of compensation information within the hospital although the information is not publicly available. As in most organizations, people care about their relative compensation and thus are incentivized to seek information about others' compensation through informal communication channels. We expect this to be the case in our setting.

[12] The cost data is at an aggregated level and does not separate out direct costs from hospital overhead costs.

[13] In our sample, only four department heads (out of 34) are female.

individuals, which includes heads and subordinates, is 16. The ratio of variable bonus to fixed pay at the department level is 2.5 (see Table 1), suggesting that bonuses are an economically meaningful part of total compensation.[14] Each department head's average salary is about twice the average salary of subordinates (see Table 3). There are 230 unique physicians and 290 unique nurses in our sample.

<Insert Table 1 here>

2.3.3. Variable Measurement

Explanatory Variable: Managerial Ability

Department heads are the unit of analysis. They all have the same formal authority to make department bonus pool allocation decisions; what varies between the department heads is their ability. Given prior research demonstrating that the number of 'stars' (i.e. a proxy for ability) in a team influences team performance, we take also measure of subordinates' ability (Groysberg et al. 2011). We compute the ability of the head and of her subordinates. We have two ways to account for subordinates' ability in our analyses: (1) including heads' own ability and subordinates' ability (as a control variable) and (2) including the ability of heads relative to their subordinates's ability, namely relative ability. We compute the relative ability poxy by measuring the distance between the head's credentials and those of the subordinates.

Our ability proxies use observable markers of ability, namely verifiable indicators of expertise, competence, reputation and experience. Based on prior research, we use age, tenure, education level, and the ranking of the graduate school at which the individual completed his degree as indicators of ability (Finkelstein 1992; Bunderson 2003). Table 2 presents descriptive statistics on these indicators. Age and tenure reflect experience; similarly, education level and the graduate school ranking capture competence or expertise in an individual's professional domain. We also use the number of prizes won, the number of

[14] The size of the bonus relative to the fixed salary is consistent with the evidence in Cooke (2004).

memberships in professional associations, and whether a given individual is identified as a 'star' physician on the hospital's website to capture the professional prominence. Together, we have seven indicators of ability, which are listed in Appendix 1.

We construct our empirical measure of "*Ability*" as follows. First, we perform a principal component analysis (promax rotation) on the seven indicators using the physician sample, which includes both heads and subordinate physicians.[15] The seven indicators load on three factors, labeled *Prestige*, *Experience*, and *Education*. The rotated factor pattern (untabulated) is consistent with the correlation among the seven ability indicators (see Table 2, Panel A); *Membership*, *Prize*, and *Star* are highly correlated and load on the factor we label "*Prestige*"; *Tenure* and *Age* load on the factor we label *Experience*; *Edu_level* and *Edu_ranking* load on the factor we label *Education*. The three factors explain more than 80% of the variation in the seven indicators.

<Insert Panel A of Table 2 here>

Next, we compute the factor score on each factor for each physician. Hence, each physician in the sample has three factor scores, namely for (1) *Prestige*, (2) *Experience*, and (3) *Education*. Note that these factor scores have been standardized and allow for comparison, but the absolute value of these score does offer an economic interpretation. After computing the factor scores of each physician, we use two different methods to create the head's ability measure: (1) the aggregate ability for heads and subordinates and (2) the relative ability (*Ability_Gap*) on each factor. Figure 1 in Appendix 2 schematically illustrates the way in which we construct *Ability* by using the head's and subordinates' ability scores.

<Insert Figure 1 here>

[15] Presumably, department heads have professional skills similar to other physicians, but not to nurses. Nurses typically do not have the capacity to decide on the medical treatment or coordinate physicians. Thus, we do not include "nurses" when constructing our empirical measure of ability.

The head's aggregate ability (*Head_Ability*) is the sum of her raw ability score across three factors, *Head_Prestige*, *Head_Experience*, and *Head_Education*. Similar to the head's aggregate ability, the subordinate physicians' aggregate ability (*Sub_Ability*) is the sum of *Sub_Prestige, Sub_Experience*, and *Sub_Education*. We use *Ability_Gap* (i.e., the "relative" ability) to describe the head's ability relative (*Head_Ability*) to that of the subordinate physicians (*Sub_Ability*). *Ability_Gap* is the difference between the head's and the subordinate physicians' aggregate abilty scores. Each head ultimately has six related ability scores to construct her *Ability_Gap, Head_Prestige*, *Head_Experience*, *Head_Education, Sub_Prestige, Sub_Experience*, and *Sub_Education*. Given that the head's relative ability can be described vis-à-vis the ability of any member of subordinate physicians, we take the maximum score on each factor among *subordinate physicians* for each department as the subordinates' ability score.

Clearly, managers' ability does not vary much over time. Given this time invarient feature of managers' ability, our empirical tests do not rely on change in ability but exploit the variations in ability "between" department heads (i.e., cross-sectional tests).

Relational Contracts: Discretionary Bonus Decisions

To understand the association between managers' ability and the relational contracts, it is important to capture the component of a bonus that best reflects managers' choice of relational contracts. Recall that the head determines her own bonus; we want to determine if she allocates herself an abnormally large share or a lower share. For the allocation bonus decision for subordinates we also need a benchmark that will determine the degree of differentiation from what would normally be expected. Thus, we use the *abnormal* bonus to capture the part of bonus which deviates from what each individual expects to earn. Based on each individual's abnormal bonus, we further construct two measures that capture (1) the abnormal size of the bonus of the manager (*Head_Abnm*) and (2) the standard deviation of abnormal size of bonus of subordinates (*Sub_Abnm*). *Head_Abnm* reflects the extent to which heads give up short-term bonus in exchange for long term gains; *Sub_Abnm* represents the degree of heads' preference for cooperation over competition among subordinates. We treat these two measures as manifestation of relational contracts.

The hospital policy states that bonuses should be based on each individual's "contribution" to the department. To separate abnormal bonus from the total bonuses, our empirical strategy is to find the objective referent distribution that might resemble a "contribution" distribution. We measure abonormal bonus as the deviation from the referent distribution. Fixed salary generally represents the average of a given individual's productivity and thus reflects their contribution to the department's performance.[16] Given that there is no objective individual performance information available from our research site, we propose that the distribution of fixed salary within the department is a reasonable approximation for the unobservable normal bonus distribution. For example, the department head usually receives a higher salary than the subordinates. Accordingly, subordinates might expect the department head to receive a bonus relative to their higher salary. The normal bonus does not contain any indication of managers' choice of relational contracts. As decribed in the bonus policy, a valid referent distribution should reflect the individuals' relative average productivity within a department.[17]

As the bonus pool and the number of employees vary across departments, we need to have a scale-free measure to capture the variations in abnormal bonus between departments. Given the departmental bonus pool system, what matters is the slice (i.e., the share) of the departmental bonus pool that each individual receives. Therefore, our computation of bonus

[16] Department heads do not have discretion in deciding the physicians' or nurses' salaries. There is a salary schedule in which the prescribed salaries vary with objective achievements that include the education level, tenure, and professional certification of a staff member.
[17] Allocating the bonus equally to each individual within a department is not a good referent distribution because it does not capture each individual's relative contribution. The fixed salary component is a reasonable proxy for this.

decisions is based on the slice measure. We use the "salary slice" (a proxy for each individual's relative contribution to the department) as the appropriate benchmark to determine the size of the abonormal bonus for both the head of the department and the subordinates within the department. We take the salary slice[18] within the department as the benchmark and take the difference between the bonus slice (*Paid_Bonus_Slice*) and the salary slice (*Salary_Slice*) as the abnormal bonus slice for each individual. We define paid bonus slice, salary slice, and abnormal bonus slice in the following equations.

$$Paid\_Bonus\_Slice_{ijt} = \frac{Paid\_Bonus_{ijt}}{\sum_{i=1}^{i=n} Paid\_Bonus_{ijt}} \tag{1}$$

$$Salary\_Slice_{ijt} = \frac{Salary_{ijt}}{\sum_{i=1}^{i=n} Salary_{ijt}} \tag{2}$$

$$Abnormal\_Bonus\_Slice_{ijt} = Paid\_Bonus\_Slice_{ijt} - Salary\_Slice_{ijt} \tag{3}$$

where subscript i represents each individual, j the department, and t the calendar month.

Turning to the measurement of managers' choices of relational contracts with two types of bonus decisions, we construct the head's abnormal bonus slice (*Head_Abnm*) as the difference between actual paid bonus slice and salary slice. With respect to the indication of cooperation or competition among subordinates, we are interested in the extent to which the department head differentiates between subordinates when allocating the remaining bonus to subordinate. We measure the department head's choices for the degree of subordinates' cooperation as the dispersion of the subordinates' abnormal bonus slices. Specifically, we compute the standard deviation of the subordinates' abnormal bonus slice within a given

[18] The salary slice is smaller than the maximum bonus slice restricted by the hospital's compensation policy. Since the salary slice is not above the enforced cap, the deviation from the salary slice is still at the manager's discretion. Salary slice is qualified to be used to determine the referent distribution.

department and use this measure as the proxy for the type of relational contracts which managers demostrate in the subordinates' bonus allocation decision (*Sub_Abnm*). We assume that each department head uses the salary slice as the "referent distribution," but we recognize that this may not be the case in practice. However, since we are interested in variations in managers' choice of relational contracts across department heads, holding our computation of abnormal bonus constant across departments helps to capture the variation in managers' choices.

2.3.4. Descriptive Statistics

Panel B of Table 2 shows the descriptive statistics of the ability measures. The department head's score on the *Prestige* factor (1.51) is higher on average than the subordinates' (−0.08). However, this is not the case for *Experience* and *Education* factors. Evidently, to the extent that the ability of heads and subordinates differs, *Prestige* is the root cause.

<Insert Panel B of Table 2 here>

Table 3 presents the descriptive statistics of the bonus allocation. Panel A of Table 3 shows that the average proportion that the department heads keep for themselves (*Paid_Bonus_Slice*) is 21%. The average maximum bonus percentage prescribed by hospital policy would amount to 26% (untabulated). In other words, the department heads, on average, do not award themselves the maximum amount possible. Panel C of Table 3 also shows that high-ability heads on average allocate a lower bonus to themselves and differentiate less among their subordinates than low-ability heads.

<Insert Table 3 here>

Table 4 presents the Pearson correlations among variables. There is a negative and significant relation between department head's relative ability (*Ability_Gap*) and the manifestation of relational contracts in two types of discretionary bonus decisions

(*Head_Abnm*, r =−0.36, p<0.01; *Sub_Abnm*, r =−0.14, p<0.01). This finding too is consistent with our hypothesis that high-ability managers (low-ability managers) prefer to maintain an ongoing relational contracts (a period-by-period relational contract).

<Insert Table 4 here>

2.4. Empirical Models and Results

We describe the empirical models and the findings for hypotheses H1 and H2 in *Ability and Discretionary Bonus Decisions* before turning to the tests regarding the performance implications of managers' ability in *Performance Effect of Ability*.

2.4.1. Managerial Ability and Discretionary Bonus Decisions

We test whether differences in ability between heads explain their discretionary bonus decisions. We use the abnormal component of managers' bonus decisions as the dependent variable and ability as the variable of interest. We have two models with different dependent variables. First, we use the head's abnormal bonus slice (i.e., *Head_Abnm*). Second, we use the standard deviation of subordinates' abnormal bonus slice (i.e., *Sub_Abnm*). We specify our two empirical models for H1 and H2 as follows:

$$Head\_Abnm_{jt}=\alpha_0 + \alpha_1\, Ability_{jt}+ \alpha_2\, Dep\_Profit_{jt}+\alpha_3\, Dep\_Size_{jt} + \alpha_4\, Physician\_ratio_{jt} + \alpha_5\, Dep\_Medicine_j + \alpha_6\, Dep\_Surgery_j + \varepsilon_{jt} \quad (4)$$

$$Sub\_Abnm_{jt}= \beta_0 + \beta_1\, Ability_{jt}+ \beta_2\, Dep\_Profit_{jt}+ \beta_3\, Dep\_Size_{jt} + \beta_4\, Physician\_ratio_{jt} + \beta_5\, Dep\_Medicine_j + \beta_6\, Dep\_Surgery_j + \varepsilon_{jt} \quad (5)$$

where subscript j represents each department, and t the calendar month. Models (4) and (5) are estimated at the department level by pooled OLS regression with robust standard errors clustered by department.

We include as control variables measures of the department's current performance, department size, and other department characteristics because these variables might systematically affect managers' decisions on abnormal bonus. We include current department profit (*Dep_Profit*), which determines the bonus pool. We include the department size, the number of physicians and nurses (*Dep_Size*) and the proportion of physicians (*Physician_ratio*). Finally, we use two proxy variables, *Dep_Medicine* and *Dep_Surgery*, to capture any task, clinical, or risk differences between departments that have the potential to influence discretionary bonus decisions. Finally, we include year fixed effects.[19]

We have four specifications that differ with respect to the measure of ability. First, we include the heads' and subordinates' aggregate ability scores (e.g., *Head_Ability* and *Sub_Ability*). Second, we include the heads' and subordinate's raw ability scores on three factors. In this specification, there are six variables: *Head_Prestige*, *Head_Experience*, *Head_Education*, *Sub_Prestige*, *Sub_Experience*, and *Sub_Education*. Third, we include the heads' relative ability scores on three factors, namely *Ability_Gap_Prestige*, *Ability_Gap_Experience*, and *Ability_Gap_Education*. Fourth, we include a single relative ability measure, *Ability_Gap*.

We base our prediction and interpretations on the first specification where controlling for subordinates' ability (*Sub_Ability*) we examine the association between departmental heads' ability (*Head_Ability*) and discretionary bonus decisions. Hypotheses H1 and H2 predict that *Head_Ability* is negatively associated with *Head_Abnm* and *Sub_Abnm*, respectively.

While we did not hypothesize the effect of the head's relative ability on the abnormal bonus of the head's discretionary bonus decisions separately, it is straightforward to predict that the head's relative ability is negatively correlated with the abnormal component of the head's discretionary bonus decisions given that the head's relative ability is the difference between the head's and the subordinates' aggregate ability.

[19] We check whether our results are sensitive to the inclusion of month fixed effects, which potentially capture the impact of hospital-wide profits on the discretionary bonus decisions. Untabulated results are qualitatively the same as reported in the primary tables. Details are available upon request.

The results of Models (4) and (5) are generally consistent with our hypotheses. With respect to the abnormal bonus that the head keep to herself, we hypothesize that *Head_Ability* is negatively associated with *Head_Abnm*. Table 5 (Panel A) reports the findings of the four specifications of Model (4). The results in column (1) of Table 5 Panel A show separate effects of the head's and the subordinates' aggregate ability. In column (1), the coefficient for *Head_Ability* is significantly negative (−1.102, p<0.01). Heads with high aggregate ability have lower abnormal bonus slices than heads with low aggregate ability. While the head's aggregate ability (*Head_Ability*) reduces *Head_Abnm*, the subordinate's aggregate ability (*Sub_Ability*) increases *Head_ Abnm* (0.850, p<0.1). This result shows that it is not only the head's ability but also the subordinates' ability that matters when managers decide on the type of the relational contracts. Consistent with our H1, keeping all else equal, when dealing with subordinates with the same ability, high-ability heads retain a smaller abnormal bonus slice than low-ability heads.

<Insert Panel A of Table 5 here>

Overall, the negative relationship between *Head_Ability* and *Head_Abnm* is consistent with our hypothesis. Heads with high ability prefer to give up more bonus to subordinates in exchange for future return than heads with low ability, and hence they retain a smaller abnormal bonus slice than heads with low ability.

With respect to the bonus decisions in differentiating between subordinates, we hypothesize that a head's ability reduces the degree of discretionary differentiation in subordinates' bonus. The results of Model (5) are reported in Panel B of Table 5. In column (1), the coefficient for *Head_Ability* is significantly negative (−0.198, p<0.01). Column (1) indicates that the head with high aggregate ability (*Head_Ability*) differentiates between subordinates to a lesser extent than the head with low aggregate ability. However, unlike our findings for the head's abnormal bonus slice (*Head_Abnm*), the subordinates' aggregate ability (*Sub_Ability*) does not affect the head's decisions in differentiating between subordinates' bonuses.

<Insert Panel B of Table 5 here>

Overall, the negative relationship between *Head_Ability* and *Sub_Abnm* is consistent with our hypothesis. Heads with high ability do not want to encourage competition among subordinates when they maintain an ongoing relational contract and hence differentiate between the subordinates' bonuses to a lesser extent than heads with low ability choosing a period-by-period relational contracts within their department.

As a whole, the findings support our prediction that the head's ability is negatively associated with (1) the abnormal bonus slice they keep to themselves and (2) the extent to which they differentiate when allocating bonuses among subordinates. We interpret those findings as evidence that high-ability managers maintain an ongoing relational contract by rewarding themselves less and differentiating subordinates less, and that low-ability managers are constrained to a period-by-period relational contracts where they reward themselves more and differentiate their subordinate more.

2.4.2. Performance Effects of Managerial Ability

We hypothesize that managers' ability is associated with the type of relational contracts, and their choice will ultimately influence departmental performance. We are interested in the performance effect of different types of relational contracts. However, relational contracts are unobservable and discretionary bonus decisions only capture part of the contracts. To evaluate the performance implications, we test the performance effects of managers' ability which drives the choice of relational contracts.[20] We use managers' ability as the independent variable, and financial performance (i.e., *Dep_Revenue and Dep_Profit*)

[20] Relational contracts are unobservable, and discretionary bonus decisions only capture part of the contracts. In that sense, managers' ability is a better proxy for the choice of relational contracts.

as the dependent variable.[21] We use Model (6) to test the performance consequences of discretionary bonus decisions.

$$Performance_{jt} = \gamma_0 + \gamma_1 Ability_{jt} + \gamma_2 Dep\_Size_{jt} + \gamma_3\, Physician\_ratio_{jt} + \gamma_4\, Dep\_Medicine_j + \gamma_5\, Dep\_Surgery_j + \varepsilon_{jt} \qquad (6)$$

where subscript *j* represents each department, and *t* the calendar month. Model (6) is estimated at the department level by pooled OLS regression with robust stand errors clustered by department. The control variables are similar to those in Models (4) and (5).

Note that Model (6) only shows the association between performance and managers' ability, but does not allow us to draw any causality between them. We predict a positive association between the head's ability and performance (i.e., γ_1>0).

Since subordinates' ability might affect managers' discretionary bonus decisions, we take this factor into account when evaluating performance implications of managers' ability. We present the empirical results of Model (6) in Table 6. Panels A and B of Table 6 present the details of our estimations with the departmental profit (*Dep_Profit*) and the departmental revenue (*Dep_Revenue*) as the dependent variable, respectively.

We treat ability either as a continuous variable in columns (1) and (2) or a binary viable in column (3) in each panel. In columns (1) and (2) of each panel, we do not find significantly positive association between managers' ability and departmental performance, either *Dep_Profit* or *Dep_Revenue*. However, when we treat managers' relative ability as a binary variable in column (3), we find that managers with high relative ability are associated with higher departmental profits and revenues, respectively (0.046, p<0.1 Panel A; 0.187, p<0.1 Panel B). Recognizing the multi-dimensional performance of the hospital and the concern with different time horizons, Table 6 provides limited evidence on the performance effect of managers' ability. However, the evidence is consistent with the prediction that high

[21] Hospitals are not only concerned with financial performance, but also with the quality of treatment and operating efficiency. However, we do not have access to these data.

managerial ability (associated with ongoing relational contracts) is associated with better organizational performance than low managerial ability (jointly with period-by-period relational contracts).

<Insert Table 6 here>

2.4.3. Discussions of Alternative Explanations

The theoretical foundations of our study are based on the assumption that 'ability' determines the choices managers make in determining bonus allocations. We view these choices as a manifestation of different types of relational contracts. Our arguments are based on Gibbons and Henderson's (2012) description of the Trust game. The major limitation of our empirical design is that we do not have a direct measure of the relational contracts in force. Alternative arguments are plausible for both types of bonus decisions. We discuss our empirical findings in relation to prior literature on the association between personal characteristics and discretionary bonus decisions. As managerial ability is correlated with their power and reputation, we assess whether these two alternative personal characteristics explain our findings.

Managerial power theory (MPT) would predict that the powerful managers are able to seek rents for themselves, so they will keep more bonuses for themselves (Bebchuk et al. 2011). However, our empirical finding that high ability managers keep a smaller share of bonus for themselves than low ability mangers is contradictory to what MPT predicts.

Another possible mechanism is the disciplining effect of reputation. Reputable managers are concerned about potential adverse economic consequence derived from their reputation loss (e.g., lower likelihood of career advancement or fewer outside opportunities), so they will avoid rewarding themselves with "excessive" bonus (Kuhnen and Niessen 2012). In other words, reputable managers will keep less bonus to themselves than managers with low reputation. However, it is not clear how managers' reputation affect the way managers allocate bonus to their subordinates. One possible prediction is that high reputation allows managers to justify their discretionary bonus decisions and they are more able to create tournament incentives with larger bonus differentials among employees. This conjecture results in the positive association between managers' reputation (ability) and the degree of bonus differentials among subordinates, which is inconsistent with our finding.

In sum, neither managerial power nor reputation explains our empirical findings on both types of bonus decisions in a consistent way. Although our empirical analyses are subject to some limitations, we do not find that alternative explanations explain our empirical findings.

2.5. Conclusion

The primary purpose of this study is to examine whether managerial ability influences the choice of relational contracts as manifested in discretionary bonus decisions. Data from a large hospital in China allow us to study this relation. The hospital grants decision rights to clinical managers of departments to allocate bonuses both to themselves and to their subordinates. Ability is particularly salient in professionally dominated organizations such as hospitals and is thus likely to be an important determinant of behavior.

In our setting we find that high-ability managers keep less abnormal bonus slice and differentiate their subordinates to a lesser extent than low-ability managers. Theoretical predictions relating to relational contracts are consistent with these findings. In essence, higher ability managers not only have the expertise and judgment to implement repeated relational contracts which require collaboration and cooperation among employees in the long run, they have the patience to wait for the long term benefits that accrue from these contracts. The bonus decision allows the manager to establish the informal agreement within the department that long run actions are desired and that the returns from such actions will accrue higher payoffs than short run actions.

Based on descriptions of the Trust game, we would expect that ongoing relational contracts, implemented to create a collaborative working environment, would deliver greater long term benefits for the department/hospital than a competitive environment. While we are not able to design a direct test on the association between performance and relational contracts, our results do provide support for prior research demonstrating that 'ability' is correlated to positive economic outcomes (Dohmen et al. 2010).

Our study contributes to prior research in a number of ways. First, we shed some light on one dimension of relational contracts by examining how different types of managers influence the choices made in the implementation of relational contracts. We contribute to empirical research on performance evaluation and compensation design, particularly those studies concerned with subjectivity (Bol 2011; Ederhof 2010). We also contribute to more recent research in accounting on the effect of managerial traits on economic decisions (Jia et al. 2014; Benmelech and Frydman In press) and the literature examining how 'ability' affects managerial decision making more widely. Our study also speaks to prior research on hospitals, particularly studies concerned with the adverse consequences when physicians dominate decision making (Ramanujam and Rousseau 2006).

We limit our study to the impact of discretionary bonus decisions on the financial performance of the department; others have demonstrated that physicians with high levels of ability and expertise can have a beneficial effect on other professionals in the clinical unit as well as on the quality of the work performed (Ramanujam and Rousseau 2006; Nembhard and Edmondson 2006). Our results would suggest similar conclusions; high ability physician managers are more likely to create a collaborative environment focused on long term outcomes than a competitive environment focused on short term outcomes. It is unclear from our limited performance data what is most desirable from the perspective of the hospital.

A potential limitation of our study is that we use data from one large hospital in China. However, we have no reason to believe that our findings would not hold in other large hospitals where the decision-making structure is dominated by highly trained physicians. We only measure financial performance outcomes. Data restrictions did not enable us to measure quality outcomes at the department level, although future research could incorporate both efficiency and effectiveness outcomes. Despite these potential limitations, this study introduces the idea into the accounting literature that ability is important in discretionary bonus decisions.

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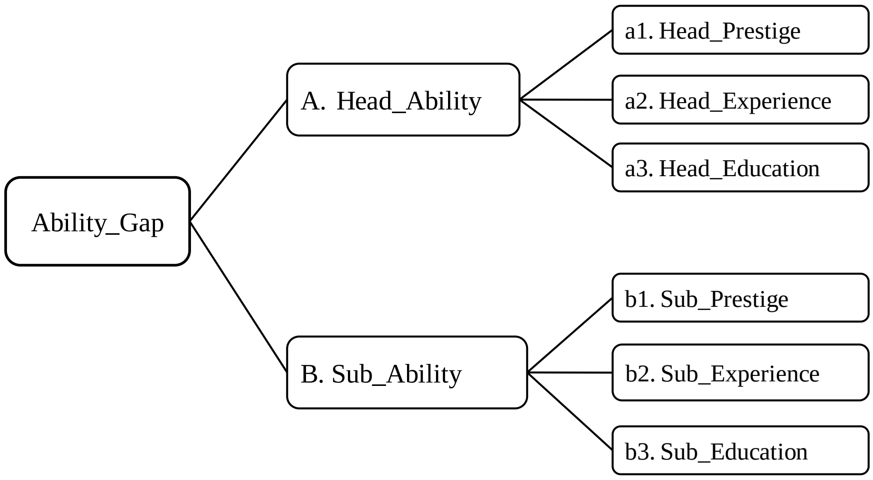
Appendix 1: Definitions of Ability Indicators

Factors of Ability	Variable	Description
Prestige	Membership	The number of memberships of medical professional associations, which is shown on the hospital's website
	Prizes	The number of prizes, which is shown on the hospital's website
	Star	Dummy variable, 1 if the hospital's website indicates the individual is a star
Education	Edu_level	Education level, ranges from doctoral degree (100) to high school diploma (60).[22] The larger value means higher education level.
	Edu_ranking	Based on the top 100 medical schools in China, the indicator ranges from 0 to 100. 100 represents the best medical school. Any medical school not listed in the top 100 medical schools is coded 0. The larger value means higher ranking of the school.
Experience	Tenure	The number of years employed at the hospital
	Age	The individual's age

[22] Those employees with high school diplomas work in medical support departments and have special skills in operating the equipment and analyzing the images.

Appendix 2: Ability Composition

Figure 1
Conceptual Framework of Ability Composition



Variable Definitions:

Ability_Gap	=Head_Ability-Sub_Ability
	=A-B
Head_Ability (A)	=the department head's aggregate ability
	=Head_Prestige+Head_Experience+Head_Education
	=a1+a2+a3
Sub_Ability (B)	=the subordinates' aggregate ability
	=Sub_Prestige +Sub_Experience +Sub_Education
	=b1+b2+b3
Ability_Gap_Prestige	=the department head's relative ability on Prestige factor
	=Head_Prestige-Sub_Prestige
	=a1-b1
Ability_Gap_Experience	=the department head's relative ability on Experience factor
	=Head_Experience-Sub_Experience
	=a2-b2
Ability_Gap_Education	=the department head's relative ability on Education factor
	=Head_Education-Sub_Education
	=a3-b3

Appendix 3: Variable Descriptions

Variable	Description
Dep_Profit	=the current departmental profit
Dep_Revenue	=the department monthly revenue
Dep_Bonus_Pool	=the department bonus based on department monthly performance =sum of the all individuals' bonus in the department
Dep_Sum_Salary	=sum of the all individuals' salary in the department
Paid_Bonus_Slice	=the ratio of each individual's bonus to the sum of all individuals' bonus in the department
Salary_Slice	=the ratio of each individual's salary to the sum of all individuals' salary in the same department
Abnm_Bonus_Slice	=Abnormal bonus slice=Paid_Bonus_Slice-Salary_Slice
Head_Dis	=the head's abnormal bonus slice, which is the difference between the head's actual bonus slice and her salary slice
Sub_Dis	=the standard deviation of subordinates' abnormal bonus slice
Head_Prestige	=the department head's factor score on Prestige factor
Head_Experience	=the department head's factor score on Experience factor
Head_Education	=the department head's factor score on Education factor
Sub_Prestige	=the subordinates' factor score on Prestige factor
Sub _Experience	=the subordinates' factor score on Experience factor
Sub _Education	=the subordinates' factor score on Education factor
Ability_Gap_Prestige	=the department head's relative ability on Prestige factor
Ability_Gap_Experience	=the department head's relative ability on Experience factor
Ability_Gap_Education	=the department head's relative ability on Prestige factor
Head_Ability	=the department head's aggregate ability
Sub_Ability	=the subordinates' aggregate ability
Ability_Gap	=the department head's aggregate ability relative to the subordinates
High_Ability	=Dummy variable, 1 if the Ability_Gap is larger than the median; other wise 0
Dep_Size	= the total number of subordinates including physicians and nurses
N_physician	=the number of physicians
N_nurse	=the number of nurses
Physician_ratio	=N_physician/Dep_Size
Dep_Medicine	=Dummy variable, 1 if the department is a medical department (such as Pediatrics); otherwise 0
Dep_Surgery	=Dummy variable, 1 if the department is a surgical department (such as Cardiovascular surgery); otherwise 0

Table 1 Summary Statistics on Variables at the Department Level

Variable	Mean	Std. Dev.	Minimum	Median	Maximum
Dep_Profit*	396,520	392,169	−1,790,577	302,512	3,442,268
Dep_Revenue*	1,802,587	1,274,811	37,967	1,555,671	7,576,272
Dep_Bonus_Pool*	116,697	89,448	1,205	91,949	681,808
Dep_Sum_Salary*	46,060	27,749	5,124	39,650	183,489
Head_Abnm	4.85	5.84	−22.06	3.59	24.51
Sub_Abnm	2.02	1.72	0.31	1.57	16.92
Dep_Size	15.58	9.43	2	13	41
N_physician	7.33	4.04	2	7	22
N_nurse	8.25	6.74	0	7	27

*The values of Dep_Profit, Dep_Revenue, Dep_Bonus_Pool, and Dep_Sum_Salary have been rescaled because of confidentiality. The monetary unit is RMB (￥).

Variable Definitions

Dep_Profit	=the departmental profit, which is the basis for bonus pool calculation
Dep_Revenue	=the department monthly revenue
Dep_Bonus_Pool	=the department bonus based on department monthly performance
	=the sum of the all individuals' bonus in the department
Dep_Sum_Salary	=the sum of the all individuals' salaries in the department
Head_Abnms	=the head's discretionary bonus slice
Sub_Abnm	=the standard deviation of the subordinates' discretionary bonus slice
Dep_Size	=the total number of subordinates including physicians and nurses
N_physician	=the number of physicians
N_nurse	=the number of nurses

Table 2 Summary Statistics on Ability Indicators (Physician Sample)
Panel A: Correlation among Ability Indicators

	Membership	Prize	Star	Edu_level	Edu_ranking	Tenure	Age
Membership	1						
Prize	0.61 (0.00)	1.00					
Star	0.63 (0.00)	0.79 (0.00)	1.00				
Edu_level	0.04 (0.00)	0.04 (0.00)	0.08 (0.00)	1.00			
Edu_ranking	0.11 (0.00)	0.10 (0.00)	0.13 (0.00)	0.52 (0.00)	1.00		
Tenure	0.16 (0.00)	0.14 (0.00)	0.10 (0.00)	−0.33 (0.00)	−0.27 (0.00)	1.00	
Age	0.18 (0.00)	0.17 (0.00)	0.13 (0.00)	−0.28 (0.00)	−0.21 (0.00)	0.94 (0.00)	1.00

P-values are in parentheses.

Panel B: Summary Statistics on Ability Measure (Factor Score) (N=1,422)

Variable		Mean	Std. Dev.	Minimum	Median	Maximum
a1	Head_Prestige	1.51	2.15	−0.28	0.68	5.80
a2	Head_Experience	0.65	0.54	−0.41	0.60	2.02
a3	Head_Education	0.16	0.81	−1.96	0.55	1.98
A	Head_Ability	2.32	2.52	−1.58	1.60	8.52
b1	Sub_Prestige	−0.08	0.43	−0.26	−0.24	1.48
b2	Sub_Experience	1.02	0.75	−1.15	1.09	2.37
b3	Sub_Education	1.23	0.89	−1.96	0.88	3.21
B	Sub_Ability	2.17	1.20	−1.58	2.35	4.64
a1-b1	Ability_Gap_Prestige	1.59	2.07	−0.94	0.01	6.04
a2-b2	Ability_Gap_Experience	−0.37	0.79	−2.17	−0.32	1.22
a3-b3	Ability_Gap_Education	−1.07	1.09	−2.70	−1.12	2.33
A- B	Ability_Gap	0.15	2.16	−3.08	−0.59	5.83

Table 3 Bonus and Bonus Slice

Panel A: Head Sample (N=1,422)

Variable	Mean	Std. Dev.	Minimum	Median	Maximum
Salary* (￥)	5,345	1,637	2,420	5,421	9,389
Paid_Bonus* (￥)	17,426	7,878	294	16,343	63,910
Paid_Bonus_Slice (%)	21.09	14.08	3.72	17.45	77.62
Salary_Slice (%)	16.24	10.61	2.88	13.34	54.88
Abnm_Bonus_Slice (%)	4.85	5.84	−22.06	3.59	24.51

*The values of Salary and Paid_Bonus have been rescaled because of confidentiality.

Panel B: Subordinate Sample (Physicians and Nurses) (N=21,020)

Variable	Mean	Std. Dev.	Minimum	Median	Maximum
Salary* (￥)	2,786	577	223	2,704	6,996
Paid_Bonus* (￥)	6,802	3,538	0	6,246	42,859
Paid_Bonus_Slice (%)	5.65	4.66	0.00	4.35	64.50
Salary_Slice (%)	5.98	5.01	0.17	4.52	52.26
Abnm_Bonus_Slice (%)	−0.33	2.13	−25.71	−0.25	23.53

*The numbers of Salary and Paid_Bonus have been rescaled because of confidentiality.

Panel C: Descriptive Statistics of Differences between High and Low Ability Sample

Variable	High-Ability (Ability_Gap>median)		Low-Ability (Ability_Gap<median)		*t*-test
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Mean
Dep_Profit*	478,897	420,698	313,211	341,671	165,685 ***
Dep_Revenue*	2,142,829	1,444,308	1,458,494	962,047	684,335 ***
Head_Abnm	2.84	5.51	6.88	5.46	−4.04 ***
Sub_Abnm	1.67	1.20	2.39	2.09	−0.72 ***
Dep_Size	16.75	8.98	14.39	9.73	2.36 ***
N_physician	7.98	4.64	6.67	3.20	1.30 ***
N_nurse	8.77	6.43	7.72	7.01	1.05 ***

*The values of Dep_Profit, and Dep_Revenue have been rescaled because of confidentiality. The monetary unit is RMB (￥). *,**,*** Indicate statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Variable definitions: See Appendix 3.

Table 4 Pearson Correlation Table (N=1,422)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)	(m)	(n)	(o)	(p)	(q)	(r)	(s)	(t)
(a)Dep_Profit	1																			
(b)Dep_Revenue	0.72 (0.00)	1																		
(c)Dep_Bonus_Pool	0.78 (0.00)	0.75 (0.00)	1																	
(d)Paid_Bonus	0.60 (0.00)	0.47 (0.00)	0.63 (0.00)	1																
(e)Salary	0.29 (0.00)	0.36 (0.00)	0.28 (0.00)	0.24 (0.00)	1															
(f)Dep_Size	0.57 (0.00)	0.65 (0.00)	0.82 (0.00)	0.20 (0.00)	0.31 (0.00)	1														
(g)N_physician	0.62 (0.00)	0.50 (0.00)	0.67 (0.00)	0.19 (0.00)	0.27 (0.00)	0.79 (0.00)	1													
(h)N_nurse	0.44 (0.00)	0.60 (0.00)	0.74 (0.00)	0.17 (0.00)	0.27 (0.00)	0.93 (0.00)	0.50 (0.00)	1												
(i)Paid_Bonus_Slice	−0.41 (0.00)	−0.57 (0.00)	−0.57 (0.00)	−0.06 (0.02)	−0.37 (0.00)	−0.76 (0.00)	−0.63 (0.00)	−0.68 (0.00)	1											
(j)Head_Abnm	−0.22 (0.00)	−0.34 (0.00)	−0.30 (0.00)	0.14 (0.00)	−0.65 (0.00)	−0.48 (0.00)	−0.42 (0.00)	−0.42 (0.00)	0.73 (0.00)	1										
(k)Sub_Abnm	−0.36 (0.00)	−0.38 (0.00)	−0.40 (0.00)	−0.10 (0.00)	−0.28 (0.00)	−0.52 (0.00)	−0.42 (0.00)	−0.47 (0.00)	0.50 (0.00)	0.31 (0.00)	1									
(l)Head_Prestige	0.30 (0.00)	0.28 (0.00)	0.21 (0.00)	0.25 (0.00)	0.52 (0.00)	0.15 (0.00)	0.31 (0.00)	0.02 (0.37)	−0.18 (0.00)	−0.37 (0.00)	−0.19 (0.00)	1								
(m)Head_Experience	0.00 (0.85)	−0.04 (0.12)	−0.04 (0.13)	0.05 (0.08)	0.16 (0.00)	−0.07 (0.01)	0.01 (0.66)	−0.10 (0.00)	0.00 (0.88)	−0.07 (0.01)	0.07 (0.01)	0.05 (0.04)	1							
(n)Head_Education	0.05 (0.05)	0.17 (0.00)	0.02 (0.38)	0.09 (0.00)	0.40 (0.00)	0.07 (0.01)	−0.09 (0.00)	0.15 (0.00)	−0.22 (0.00)	−0.25 (0.00)	−0.38 (0.00)	0.23 (0.00)	−0.19 (0.00)	1						
(o)Sub_Prestige	−0.14 (0.00)	−0.24 (0.00)	−0.17 (0.00)	−0.01 (0.66)	0.09 (0.00)	−0.18 (0.00)	−0.12 (0.00)	−0.17 (0.00)	0.07 (0.01)	−0.07 (0.01)	0.02 (0.48)	0.29 (0.00)	0.44 (0.00)	−0.01 (0.85)	1					
(p)Sub_Experience	0.23 (0.00)	0.15 (0.00)	0.27 (0.00)	0.16 (0.00)	0.05 (0.09)	0.22 (0.00)	0.32 (0.00)	0.12 (0.00)	−0.24 (0.00)	−0.08 (0.00)	−0.18 (0.00)	0.22 (0.00)	0.28 (0.00)	0.03 (0.20)	0.21 (0.00)	1				
(q)Sub_Education	0.35 (0.00)	0.43 (0.00)	0.36 (0.00)	0.27 (0.00)	0.24 (0.00)	0.37 (0.00)	0.33 (0.00)	0.33 (0.00)	−0.38 (0.00)	−0.20 (0.00)	−0.28 (0.00)	0.33 (0.00)	−0.15 (0.00)	0.18 (0.00)	−0.09 (0.00)	−0.13 (0.00)	1			
(r)Head_Ability	0.27 (0.00)	0.29 (0.00)	0.18 (0.00)	0.25 (0.00)	0.61 (0.00)	0.14 (0.00)	0.24 (0.00)	0.05 (0.08)	−0.22 (0.00)	−0.41 (0.00)	−0.27 (0.00)	0.94 (0.00)	0.20 (0.00)	0.48 (0.00)	0.34 (0.00)	0.26 (0.00)	0.30 (0.00)	1		
(s)Sub_Ability	0.36 (0.00)	0.33 (0.00)	0.38 (0.00)	0.30 (0.00)	0.24 (0.00)	0.35 (0.00)	0.40 (0.00)	0.25 (0.00)	−0.41 (0.00)	−0.23 (0.00)	−0.32 (0.00)	0.48 (0.00)	0.22 (0.00)	0.16 (0.00)	0.42 (0.00)	0.60 (0.00)	0.63 (0.00)	0.51 (0.00)	1	
(t)Ability_Gap	0.12 (0.00)	0.15 (0.00)	−0.00 (0.99)	0.13 (0.00)	0.58 (0.00)	−0.04 (0.16)	0.06 (0.04)	−0.09 (0.00)	−0.03 (0.20)	−0.36 (0.00)	−0.14 (0.00)	0.83 (0.00)	0.11 (0.00)	0.47 (0.00)	0.16 (0.00)	−0.03 (0.22)	0.00 (0.85)	0.88 (0.00)	0.04 (0.12)	1

Table 5 Regressions of Two Types of Abnormal Bonus on Ability

Panel A: Regression of the Head's Abnormal Bonus on Ability

$$Head\_Abnm_{jt}=\alpha_0 + \alpha_1\, Ability_{jt}+ \alpha_2 Dep\_Profit_{jt}+ \alpha_3 N\_physician_{jt}+ \alpha_4\, N\_nurse_{jt} + \alpha_5\, Dep\_Medicine_j+ \alpha_6\, Dep\_Surgery_j + \varepsilon_{jt} \qquad (4)$$

Robust standard error is clustered at the department level and reported in parenthesis. We construct the subordinates' ability by taking the maximum score on each factor among the subordinates. *,**,*** Indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

	Head_Abnm (1)	**Head_Abnm (2)**	**Head_Abnm (3)**	**Head_Abnm (4)**
Head_Ability	-1.102***			
	(0.218)			
Sub_ Ability	0.850*			
	(0.459)			
Head_Prestige		-1.052***		
		(0.249)		
Head_Experience		-2.828***		
		(0.999)		
Head_Education		-1.103		
		(0.803)		
Sub_Prestige		0.527		
		(1.080)		
Sub_Experience		1.600*		
		(0.892)		
Sub_Education		1.046		
		(0.740)		
Ability_Gap_Prestige			-1.092***	
			(0.233)	
Ability_Gap_Experience			-2.073***	
			(0.748)	
Ability_Gap_Education			-1.153**	
			(0.514)	
Ability_Gap				-1.115***
				(0.223)
Dep_Profit	2.604	0.810	1.301	2.202
	(2.442)	(2.162)	(2.206)	(2.399)
Dep_Size	1.610	0.876	-0.124	1.177
	(4.150)	(3.772)	(3.954)	(3.840)
Physician_ratio	-1.996	-2.718	-2.838	-2.280
	(2.712)	(3.065)	(2.387)	(2.457)
Dep_Medicine	-2.159	-3.506	-3.670*	-2.515
	(2.311)	(2.457)	(2.044)	(2.074)
Dep_Surgery	2.604	0.810	1.301	2.202
	(2.442)	(2.162)	(2.206)	(2.399)
Year fixed effects	Included	Included	Included	Included
Observations	1,422	1,422	1,422	1,422
Adjusted R^2	0.422	0.443	0.430	0.420

Table 5 Regressions of Two Types of Abnormal Bonus on Ability (continued)
Panel B: Regression of Dispersion of Subordinates' Abnormal Bonus on Ability

$$Sub\_Abnm_{jt} = \beta_0 + \beta_1 Ability_{jt} + \beta_2 Dep\_Profit_{jt} + \beta_3 N\_physician_{jt} + \beta_4 N\_nurse_{jt} + \beta_5 Dep\_Medicine_j + \beta_6 Dep\_Surgery_j + \varepsilon_{jt} \quad (5)$$

Robust standard error is clustered at the department level and reported in parenthesis. We construct the subordinates' ability by taking the maximum score on each factor among the subordinates. *,**,*** Indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

	Sub_Abnm (1)	**Sub_Abnm (2)**	**Sub_Abnm (3)**	**Sub_Abnm (4)**
Head_Ability	-0.198***			
	(0.070)			
Sub_ Ability	0.061			
	(0.077)			
Head_Prestige		-0.052		
		(0.059)		
Head_Experience		-0.206		
		(0.241)		
Head_Education		-0.739***		
		(0.187)		
Sub_Prestige		-0.187		
		(0.325)		
Sub_Experience		0.017		
		(0.129)		
Sub_Education		0.037		
		(0.117)		
Ability_Gap_Prestige			-0.164**	
			(0.071)	
Ability_Gap_Experience			-0.120	
			(0.149)	
Ability_Gap_Education			-0.376***	
			(0.132)	
Ability_Gap				(0.0775)
				(0.099)
Dep_Profit	−0.063	0.019	−0.269	−0.143
	(0.320)	(0.330)	(0.307)	(0.321)
Dep_Size	-1.342**	-1.549***	-1.838***	-1.558**
	(0.549)	(0.447)	(0.636)	(0.613)
Physician_ratio	-0.088***	-0.097***	-0.097***	-0.093***
	(0.014)	(0.014)	(0.018)	(0.017)
Dep_Medicine	-1.786	-2.042**	-1.995	-2.024
	(1.137)	(0.909)	(1.232)	(1.268)
Dep_Surgery	-2.535**	-1.848**	-2.541**	-2.674**
	(1.140)	(0.797)	(1.216)	(1.261)
Year fixed effects	Included	Included	Included	Included
Observations	1,375	1,375	1,375	1,375
Adjusted R^2	0.428	0.478	0.436	0.421

Table 6 Regression of Performance on the Heads' Ability
Panel A: Profit and Ability

$$Performance_{jt}=\gamma_0+\gamma_1 Ability_{jt}+\gamma_2 Dep\_Size_{jt}+\gamma_3\,Physician\_ratio_{jt}+\gamma_4\,Dep\_Medicine_j + \gamma_5\,Dep\_Surgery_j+\varepsilon_{jt} \quad (6)$$

Robust standard error is clustered at the department level and reported in parenthesis. We construct the subordinates' ability by taking the maximum score on each factor among the subordinates. *,**,*** Indicate statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

	Dep_Profit (1)	**Dep_Profit (2)**	**Dep_Profit (3)**
Head_Ability	0.007		
	(0.005)		
Sub_Ability	0.011		
	(0.013)		
Ability_Gap		0.008	
		(0.005)	
High_Ability			0.046*
			(0.023)
Dep_Size	0.011***	0.012***	0.011***
	(0.003)	(0.002)	(0.002)
Physician_ratio	0.056	0.091	0.060
	(0.054)	(0.054)	(0.054)
Dep_Medicine	-0.082*	-0.062	-0.085
	(0.046)	(0.052)	(0.053)
Dep_Surgery	-0.073	-0.049	-0.058
	(0.045)	(0.047)	(0.047)
Year fixed effects	Included	Included	Included
Observations	1,422	1,422	1,422
Adjusted R^2	0.522	0.508	0.515

Table 6 Regression of Performance on the Heads' Ability (continued)
Panel B: Revenue and Ability

$$Performance_{jt}=\gamma_{0}+\gamma_{1}Ability_{jt}+\gamma_{2}Dep\_Size_{jt}+\gamma_{3}\,Physician\_ratio_{jt}+\gamma_{4}\,Dep\_Medicine_{j}+\gamma_{5}\,Dep\_Surgery_{j}+\varepsilon_{jt} \quad (6)$$

Robust standard error is clustered at the department level and reported in parenthesis. We construct the subordinates' ability by taking the maximum score on each factor among the subordinates. *,**,*** Indicate statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

	Dep_Revenue (1)	**Dep_Revenue (2)**	**Dep_Revenue (3)**
Head_Ability	0.034		
	(0.023)		
Sub_Ability	0.016		
	(0.045)		
Ability_Gap		0.038	
		(0.023)	
High_Ability			0.187*
			(0.101)
Dep_Size	0.031***	0.034***	0.031***
	(0.006)	(0.005)	(0.006)
Physician_ratio	-0.366	-0.275	-0.404*
	(0.227)	(0.183)	(0.221)
Dep_Medicine	-0.044	0.007	-0.092
	(0.111)	(0.110)	(0.140)
Dep_Surgery	-0.166	-0.100	-0.146
	(0.103)	(0.091)	(0.091)
Year fixed effects	Included	Included	Included
Observations	1,422	1,422	1,422
Adjusted R^2	0.599	0.589	0.596

Chapter 3

Does Workforce Homogeneity Matter for Employee Learning and Effort?

Chapter 3: Does Workforce Homogeneity Matter for Employee Learning and Effort?[23]

3.1. Introduction

We investigate whether the homogeneity of a given firm's workforce is associated with employee learning and their provision of effort. A workforce is more homogenous when it is made up of employees who are more similar on specific characteristics. Firms face a tradeoff between the costs and benefits of workforce homogeneity. On the one hand, a more homogenous workforce facilitates communication among employees, ultimately allowing workers to learn from each other and improve mutual monitoring. On the other hand, when employees are more alike, they might find it easier to collude against their bosses, hide information and conspire to reduce effort.

We expect the effect of workforce homogeneity to depend on the unsolved control problems of incentive contracts. Firms use incentive contracts to mitigate the most salient conflicts-of-interest between employees and their principal. Even well-designed incentive contracts cannot address all agency problems, however, and we focus our attention on those which remain unsolved. We examine the effect of workforce homogeneity in a setting that offers different types of incentive contracts to workers employed in either of two production environments. These two production environments are at opposite ends of the spectrum, namely a production line with individual workstations and team production in which group members perform highly-related tasks. Consequently, we study the influence of incentive contracts and production environment jointly.

[23] This chapter is co-authored with Laurence van Lent and Anne Wu.

As Baron and Kreps (2013) observe, firms may foster similarity among their employees for many reasons related to psychological or sociological complementarities. Consequently, employees more easily share information and find opportunities to work together when the workforce is more homogenous. Thus, when their jobs require significant amounts of cooperative effort or employees are in frequent contact and need to share abundant information, a more homogenous workforce reduces communication costs and facilitates cooperation (Prat 2002; Ichino and Maggi 2000). By sharing information, employees increase the scope for learning from each other's experiences. In addition, the more frequent interactions between coworkers in a homogenous workforce are likely to strengthen mutual monitoring.

Workforce homogeneity, however, raises its own set of control problems. When employees are more similar, the probability increases that they collude and "sabotage" the firm's monitoring systems (Towry 2003). Similarity also reduces the potential to learn from each other's differences, potentially hampering innovation. We argue that whether the costs or the benefits of workforce homogeneity will dominate depends on the unsolved control problem in each production environment.

We study the effects of workforce homogeneity using proprietary data from a manufacturing plant (referred to as PCM), which is located in a Special Economic Zone in China. This plant offers three features that we exploit in our tests. First, the PCM plant is structured in two different production environments (corresponding to different parts of the manufacturing process). In the first setting, workers are arranged in a production line. Each work station in the line performs a relatively stand-alone activity (with inventory buffers between stations to ensure that workers are isolated from upstream disruptions). In the production line, quality is an important and measured dimension of output. Downstream workers inspect the quality of the work done by earlier work stations. Consistent with the concern for quality in this setting, employees are subject to an individual incentive contract, in which each worker's bonus increases in individual production efficiency, but the bonus is reduced when quality is poor. When workers share their information with others in the production line, employee learning about quality improves, but sharing information also exposes coworkers to bonus penalties. By colluding with each other, employees can prevent quality information from being shared.

In the second setting, the work is organized in groups in which employees perform highly related tasks. Collaboration in the group is important for achieving desired outcomes and group members can learn about improving efficiency from the experience of working together with coworkers. In this setting, employees are subject to a group incentive contract, in which each member's bonus increases in group-level efficiency. Group incentive contracts are vulnerable to individual team members free-riding on the efforts of others. Mutual monitoring among team members, however, reduces the scope for free-riding. Group members can, however, also collude to game the system, for example by reducing effort on those aspect of performance that are not measured in the incentive system.

Second, firms in Special Economic Zones rely strongly on migrant workers, who tend to come from rural areas with few opportunities for non-agricultural employment and with limited schooling facilities. The jobs offered are usually for unskilled work, which matches the background of most migrants. Prospective workers come from across mainland China and thus have different hometowns; i.e. different places where they were born and raised. Regional differences are strong in China and extend over such important dimensions as language, food, economic development, cultural preferences, and shared history. Thus, the hometown of employees captures many of those worker attributes that we a priori expect to influence the degree of workforce homogeneity.

Third, competition for labor is fierce with demand for unskilled labor exceeding supply in the local factor markets. Firms, including PCM, employ multiple strategies to recruit new personnel. One important channel is referrals. Current workers frequently encourage job candidates to apply for a job at PCM. The literature on recruitment sources has documented that current employees seek out in particular those candidates who they believe will be a good fit with the firm (Weller et al. 2009). In addition, we rely on prior studies which show that socialization processes after the new employee has been recruited are more intense as supervisors and peers tend to pay more attention to referred employees (Zottoli and Wanous 2000). Socialization helps new employees to understand what is defined as expected behavior in the firm. In this sense, more intense socialization yields a more homogenous workforce. We thus use the recruitment channel (by referral or not) as an observable indicator for otherwise difficult to observe dimensions in which employees might be similar. A higher proportion of referred workers, then, increase workforce homogeneity.

Our setting thus provides us not only with two very different production environments, but also with two plausible empirical proxies to capture workforce homogeneity (namely, the hometown background of employees and the proportion of referred workers). To investigate the effect of workforce homogeneity on effort and learning in the two production environments, we split our sample into two samples corresponding to each setting and examine our predictions about workforce homogeneity separately *within* each sample. Throughout the study, we refer to the setting with group production and group-based incentive contracts as the *Group environment* sample (GROUP), whereas the *Production line* sample (LINE) comprises those employees working on independent activities under an individual incentive contract.

In the LINE sample, the unsolved control problem is the potential for coworkers to collude by not sharing information about quality. Information sharing, however, is a necessary ingredient for learning. We therefore examine how workforce homogeneity influences two types of learning, namely about more efficient work procedures and about quality. In the GROUP sample, the unsolved control problem is potential free riding on the efforts of team members. A more homogenous workforce is expected to improve mutual monitoring. Therefore, in this sample, we examine the effect of workforce homogeneity on effort choice. We also consider whether workforce homogeneity affects learning about efficiency. Information sharing is not an unresolved control problem in this sample, and homogeneity should improve the communication among group members necessary for learning. However, homogeneity also reduces the scope for learning from others in the group, simply because when group members have less diverse experiences from which they can learn. In GROUP, quality is not measured and therefore we cannot analyze how workforce homogeneity affects learning about quality.

Our results are broadly consistent with the hypothesis that workforce homogeneity is associated with employee learning, but we do not find evidence on the association between workforce homogeneity and the provision of effort. In the LINE sample, we find that workforce homogeneity (when measured using referral ratio) decreases learning about quality. In the GROUP sample, we find that a more homogenous workforce improves group learning about efficiency. We interpret these findings as demonstrating that studying the effects of workforce homogeneity requires finely grained data on the structural arrangements in the firm. It turns out to matter how the firm has organized the work (in teams or in a sequence of independent workstations with the associated incentive contracts). The specifics of the production environment might reverse the sign on the effect of workforce homogeneity on learning.

Our study extends the accounting literature in three ways. First, we document that workforce homogeneity has different learning consequences depending on the organization design of the firm. This finding complements Campbell (2012) who shows that firms can resolve control problems by selecting employees whose preferences are aligned with those of the firm. Building on this important insight, we document that a more homogenous workforce can have both positive and negative effects on firm performance depending on the specifics of the production environment.

Second, we highlight that workforce homogeneity does not only matter in determining the employee's effort, but also influence their learning. We document that homogeneity can both improve the communication and information exchange that is needed for learning as well as that it can harm learning (arguably) by enabling collusion with coworkers.

Third, our study provides insights relating to earlier experimental evidence on monitoring in teamwork environments (Towry 2003; Zhang 2008). This earlier work focuses on "team identity", i.e., a psychological attachment of team members to the team, and investigates the effectiveness of monitoring systems while manipulating team identity. We provide an economic perspective and argue that when team members are more homogenous, communication within the group improves and, in turn, so does employee learning. A homogenous workforce increases the likelihood that a team identity arises. At the same time, our findings show that workforce homogeneity might be less beneficial when employees are not working in a team but in individual workstations along a production line.

3.2. Hypothesis Development

3.2.1. The Effect of Homogeneity on Effort and Learning

Firms have to tradeoff the costs and benefits of workforce homogeneity. Baron and Kreps (2013) suggest that most firms are vexed by the question of how much uniformity among employees to impose across subunits and locales. The costs of imposing homogeneity on the workforce include those associated with not reflecting in the control systems the potentially varied tasks in which employees are involved. Campbell (2012) is one of the first studies to provide evidence on the potential benefits of homogeneity, namely that firms can reduce control problems by selecting employees who share the objectives of the firm. To the extent that firms are successful in this pursuit, the resulting workforce will become more homogenous—at least on the dimensions of the beliefs, values, and objectives the employees share (Van den Steen 2010). Ultimately, as the objectives of firm and workforce overlap more, the conflict of interest between bosses and subordinates abates and the firm needs to rely less on contractual solutions (such as, monitoring systems, performance measures, and incentives) to induce workers to provide effort on the job. Homogeneity may also help to establish a social norm or identity (Akerlof and Kranton 2005; Akerlof and Kranton 2008), which in turn can be beneficial to inducing employees to work (Abernethy et al. 2014).

Homogeneity of the workforce does not only affect effort through the reduction of within-firm agency problems. A more homogenous workforce is able to coordinate activities more efficiently, raising the scope for cooperation among coworkers. Homogeneity provides the common ground necessary for the exchange of ideas and information as well as for mutual support activities that strengthen the robustness of collaborative initiatives.

Workforce homogeneity, however, is not just expected to affect employee effort. Learning as well is likely a function of homogeneity. Employees can accumulate knowledge while performing their duties via both individual experience and the experience of working with others (Reagans et al. 2005). Workforce homogeneity is expected to matter foremost in the learning by working with others. Again, language is an important mechanism in this type of learning. A common language helps to improve communication efficiency (easing the task of learning to coordinate with coworkers) and facilitates the sharing of knowledge between coworkers. In a more homogenous workforce, workers will be better able to understand subtle non-verbal codes, gestures, and facial expressions. Together, this improved understanding smoothens the interaction between coworkers necessary for learning.

Learning, however, also depends on coworkers to have different knowledge and/or experience. Diversity in talents, backgrounds, and skills fosters the kind of experimentation learning theory suggests to be crucial for generating new knowledge (Hayes et al. 2006; Vanhaverbeke et al. 2006). In balance, which of these effects of workforce homogeneity on learning dominates, will depend on the specifics of the production environment. If workers conduct relatively routine, well-defined tasks in a highly standardized setting then homogeneity is likely to improve learning (given its beneficial effects on coordination and mutual understanding). In an environment that is more uncertain, featuring ambiguity and non-routine tasks that require combining knowledge and information from many different sources to create new knowledge, homogeneity plausibly harms learning.

The improved opportunities for collusion present another significant potential costs to having a more homogenous workforce. Economic theory clarifies that collusion can only be a viable equilibrium strategy if agents can enter into long-term relations that are self-enforcing

(Mookherjee 2013) Collusion is more probable among agents who for some reason believe that they can rely on the counterparty's promises to act together against the principal. Arguably, these beliefs will be stronger in case of coworkers who understand better their mutual backgrounds and (language) codes.

In sum, workforce homogeneity can reduce control problems, increase effort provision, and support employee learning. At the same time, homogeneity makes it easier for workers to collude against the principal and reduces the opportunity for workers to learn from each other's differences. In the next section, we attempt to predict which of these forces dominates in the two production environment and incentive contract arrangements available within our setting.

3.2.2. Homogeneity in the LINE Sample

The production tasks for each worker on the line are simple and require only routine actions. The key dimensions of worker output (namely their efficiency and quality) are easy to measure. Individual incentive contracts are high-powered and penalize workers if they increase efficiency at the expense of quality. Thus, in the context of PCM's line production, we do not expect that eliciting optimal effort on the job is a salient contracting problem.

At the same time, however, in the line production setting, individual productivity improvements mainly come from the worker's own experience on the job. Indeed, as all work stations perform their own unique part of the production process, co-workers do not have much relevant information about how to improve the efficiency of those tasks that are not their own. Thus, we do not expect learning about efficiency to be affected by the workforce homogeneity of the production line.

That said, in line production, "downstream" work stations receive the output of "upstream" workers. Thus, quality problems occurring earlier in the production process can be observed at later stages in the production line. Workers, in this fashion, accumulate timely, private information about upstream quality, which could be used to improve the manufacturing process. For this benefit to materialize, downstream workers need to report their private quality information to quality inspectors or shift supervisors.

The incentive contract in the LINE sample specifies a penalty for quality defects. Reporting quality problems to inspectors imposes penalties on the workers who are responsible for poor quality. In production lines with high workforce homogeneity, the opportunity for workers to collude with each other against supervisors (to withhold the quality information) is significant. Without information sharing, learning about quality will be impaired. A more homogeneous workforce increases the probability that individuals collude; reporting on poor quality reduces the bonus of co-workers, and thus decreases their welfare. By withholding this information today, workers count on receiving a reciprocal treatment in the future when their own quality might be impaired. What's more, downstream workers could mask defects or make provisionary repairs. This type of behavior is more likely when employees find it easy to communicate with each other and coordinate their exploitative actions.

In addition, private quality information is more likely to be revealed to inspectors and supervisors when disputes among co-workers in the line arise. In these cases, bosses have to intervene and settle disputes or disagreements. These kinds of frictions between workers disrupt the otherwise strong incentives to hide private quality information. Supervisors, in the course of the intervention, become more familiar with the details of the production process and obtain better insights to potential quality problems. Disputes are more likely to happen when workers come from different backgrounds, do not share each other's dialect or have different views of the world. Disputes are also more likely if employees are less successfully socialized by their coworkers. When the workforce is more heterogeneous, disputes will be more often resolved in a formal way, by involving a supervisor, rather than by informally ironing out any differences.

Taking these arguments together, our prediction is that workforce homogeneity in a given production line impairs the workers' learning about quality. Workers find it easier to coordinate their actions against the firm when they are more similar. They are more likely to prevent the leakage of quality information, which in turn will penalize their bonus payments. Learning about efficiency, on the other hand, is determined by the workers experience performing his own task and is unaffected by the homogeneity of the workforce in the same production line.

> **H1a:** (*LINE setting*) Workforce homogeneity is negatively associated with learning about quality.
>
> **H1b:** (*LINE setting*) Workforce homogeneity is not associated with learning about efficiency.

3.2.3 Homogeneity in the GROUP Sample

In the GROUP environment, employees are members of a formal working group, which is responsible for completing a distinct part of the production process. To complete the team task, employees need to work together and coordinate their individual activities. The performance of the group is measured and rewarded at the group-level only. While this joint performance measure encourages members to help each other and to "internalize" the spillover effects of their actions in the group, it also opens the door to free-riding problems (Baker et al. 1988). Individual group members bear the full costs when they increase effort, but only receive a fraction of the benefits (which decreases in the size of the group). Thus, the individual worker's effort choice is a salient problem in the GROUP sample.

One consequence of homogeneity is that it reinforces the working of peer pressure. In more homogenous groups, peer pressure is likely to be stronger and, in turn, shirking is less prevalent (Kandel and Lazear 1992). Indeed, firms are likely to spend resources on mechanisms that enforce group norms that counteract the free riding problem (Waldman 2013). Workforce homogeneity may also help to breed altruism in the workplace. Rotemberg (1994) shows that when workers are altruistic and the firm uses group incentives, each worker increases effort levels because the effect of higher effort on the pay of *other* workers is internalized. In Rotemberg's model, workers can choose to become altruistic toward specific individuals and it is more likely that such happens when team members are more alike (Pedone and Parisi 1997; Lewis 1998).

Group members improve their productivity not only by becoming more experienced in carrying out their own assigned tasks, but also by their interactions with coworkers (Mas and Moretti 2009a). In particular, group members are encouraged to share knowledge within the group and to learn about coordinating their tasks as measured performance depends on group-level output. Several studies have pointed out that team homogeneity matters as it improves communication among the members and reduces coordination problems (Prat 2002; Hamilton et al. 2003; Dahlin et al. 2005).

On the other hand, there is also evidence that productivity gains are larger when the team members are more diverse in skill (Mas and Moretti 2009; Hamilton et al. 2003). Thus, while workforce homogeneity is important to foster the socialization processes that facilitate learning and provide pressure on group members to keep up with the efforts of their coworkers, it is also necessary that workers have different skills or talents.

Our prediction about which of these two effects of homogeneity on learning dominates, uses the specifics of the research setting. Learning in the PCM setting is much more about coordinating activities and becoming more familiar with the work practices of team members, than it is about creating, say, an innovative component of a PC motherboard. Thus, in our setting, we expect that the effect of homogeneity on the ease of communication with group members dominates. We thus predict that a greater degree of homogeneity at the group-level, reduces free-riding problems and improves group learning.

> **H2a:** (*Group setting*) Workforce homogeneity is positively associated with the provision of effort at the group-level.
>
> **H2b:** (*Group setting*) Workforce homogeneity is positively associated with learning about efficiency at the group-level.

3.3. Research Setting, Empirical Measures, and Data

The research site for this study is PCM, a passive component manufacturing firm located in Shenzhen (in the Guangdong province), a Special Economic Zone on the southern coast of China. PCM was established in 2005 and produces components that are used in motherboards of personal computers. The production technology is not difficult to replicate and does not require a large upfront investment. In other words, the entry barriers to the industry are low and product-market competition is fierce. At the same time, PCM's manufacturing process is labor-intensive albeit that most employees are low-skilled. Productivity improvements occur through on-the-job learning by employees, who accumulate task-specific knowledge.

3.3.1. Local Labor Market Conditions

In China, the workforce consists of a large pool of unskilled labor with relatively low productivity (Meng 2012). Workers often leave their regions of origin in the rural areas in Western or Central China and migrate to industrial cities (in particular those located in the Special Economic Zones). Migration is the key reason for the diversity in background of workers.

As more and more firms enter China to benefit from its abundance of (cheap) labor, increasingly, personnel has become scarce in some locations. This holds true especially in Shenzen. The growing demand for labor in these Special Economic Zones has increased labor costs rapidly in the coastal areas. Indeed, in response, some firms are moving their manufacturing to western China, closer to those areas where supply is still strong.

PCM deals with these tightening conditions on the local labor market by relying on various recruitment strategies. Traditional ways to attract labor such as campus visits and the posting of vacancies on jobseeker websites are complemented with a policy that uses the current workforce to encourage job candidates to apply for a job at PCM. Current PCM workers benefit from referring new hires as having more personnel reduces the excessive workloads as well as the pressure on current employees to work overtime.

Employee turnover is high at PCM, which in part is due to the Chinese policy of *hukou* (Meng 2012). Under this policy, individuals have to register in the city where they were born. Changing the registered residence (i.e., hukou) is difficult, so it usually remains the individual's official residence. The registered residence recognizes an individual's entitlements to schooling, the right to buy real estate, as well as other social welfare benefits only within the place of residence. Thus, individuals tend to be born and raised in the same region, which we label the *hometown*. Effectively, the hukou system constrains labor mobility between urban and rural areas. As migrant workers have limited civil rights outside their hometown, they tend to not stay long in any other city.

3.3.2. Measuring Workforce Homogeneity

We propose two empirical measures of workforce homogeneity (*HMGN*). The first, *hometown homogeneity*, exploits the availability of each individual employee's *hukou* in the personnel records of the firm. Our second measure, *referral ratio*, is the fraction of referred workers in a group or specific production line.

Hometown Homogeneity (SAMEHOME)

A given individual's hometown is an official record maintained by the Ministry of Public Security that cannot easily be changed. Specifically, the record will not be modified if a person lives and works in a province outside their (original) hometown. We rely on this official record to measure a worker's hometown. Figure 1 is a map of China with the dispersion of the hometowns (in this case, the home province) of PCM workers. Table 1 provides more detailed evidence.

<Insert Figure 1 and Table 1 here>

Over 50 percent of PCM employees originate from three provinces: Guangxi (21 percent), Hunan (19 percent), and Henan (17 percent). The remainder of the workforce has a hometown in one of 16 different provinces. We construct a group-level measure (akin to the Herfindahl index of market power) of the degree of hometown homogeneity (*SAMEHOME*). In particular, we measure the size of a "hometown subgroup" in relation to a "group". In our GROUP sample, the group is defined in a straightforward manner as the members of a given team that are subject to a common performance measure of group output. However, in the LINE sample, we define the set of workers who are employed in the same production line as a "group".

$$\textit{Hometown homogeneity (SAMEHOME)} = \sum_{p=1}^{P} S_p^2 = \sum_{p=1}^{P} \left(\frac{n_p}{N} \right)^2 \quad (1)$$

S_p is the fraction of group members from province p in the group, n_p represents the number of group members from province p, and N equals the total number of group members in the group. *SAMEHOME* ranges from *1/N*, when all group members come from different provinces, to 1, when all are from the same province.

Referral Ratio (RFLratio)

We believe that the fraction of workers who join the firm based on a referral by current workers also provides a valid measure of workforce homogeneity. This belief is grounded in economic theory and in work on socialization processes. Labor markets exhibit substantial two-sided information asymmetry. Employees have limited information about possible employers and employers cannot gain complete information about job applicants (Stigler 1962). By relying on current workers to recruit new employees firms are likely to improve the match between candidates and the firm and reduce information asymmetry (Fernandez et al. 2000). Prior work on recruitment channels shows that current employees are able to provide candidates with the kind of insider information about the job that is difficult to obtain otherwise (Pieper 2014; Jovanovic 1979). Prospective employees are thus better able to decide whether they will fit the firm and get along with their future colleagues. Current workers also have incentives to ensure that the job candidates are a good match to the firm, as the applicant's performance will reflect on them.

Similar incentives exist post-hire, as the current employee works to ensure that the new entrant has the resources and information to do well. Through informal training and mentoring, referral hires experience stronger socialization (Granovetter 1973; Louis 1980). Some evidence exists that peer pressure is exerted to ensure that new entrants conform to organizational goals and to increase the likelihood that they will stay longer with the firm (Kugler 2003). Together these matching and socialization mechanisms associated with recruiting new employees through referrals are likely to produce a more homogenous workforce.

3.3.3. Compensation at PCM

PCM's worker incentive plan comprises a fixed salary and a monthly bonus. Bonuses are formula-based, but their computation differs between the two production environments. In the LINE sample, the plan awards individual workers a bonus based on their efficiency and the defect rate of their work. Specifically, efficiency is computed by comparing the standard hours allowed for actual output quantities (*Standard Labor Hours*) and the actual hours used to produce these actual outputs (*Actual Labor Hours*). The difference between standard and actual labor hours is labeled *Efficiency Points*. Analogously, the *Defect Points* are computed based on a schedule that prescribes the standard rework/repair time for each defect. The individual bonus increases with the *Efficiency Points* and decreases with the *Defect Points*. Indeed, the formula specifies that the bonus equals (*Efficiency Points * Bonus Rate*) – (*Defect Points * Penalty Rate*).

In the GROUP sample, the plans are based on efficiency only (i.e., there is no penalty for defective products). In addition, performance is measured at the group level. Thus, *Efficiency Points* are computed by comparing standard labor hours allowed for the actual group output with actual labor hours worked by the group. The group bonus equals *Efficiency Points * Bonus Rate.*

3.3.4. Measures of Outcomes

We use information from the bonus plans to compute *Efficiency* and *Quality* measures of output. Specifically, we measure *Efficiency* as the ratio of standard labor hours allowed for the actual level of output (*Standard Labor Hours*) to the actual labor hours spent on manufacturing the actual output quantities (*Actual Labor Hours*). Using fewer actual hours to produce the same amount of actual output improves *Efficiency*. PCM workers earn a bonus when *Efficiency* exceeds unity; this same value is also used to identify inefficient workers. In the LINE sample, *Efficiency* is defined at the individual level and the measure is superscripted with *L*; in the

GROUP sample, PCM measures *Efficiency* at the group-level only and we use the superscript *G*. The subscripts *i* and *g* correspond to the individual worker and specific group, respectively.

$$Efficiency_{it}^{L} = \frac{Standard\_Labor\_Hours_{it}}{Actual\_Labor\_Hours_{it}} \tag{2.1}$$

$$Efficiency_{gt}^{G} = \frac{Standard\_Labor\_Hours_{gt}}{Actual\_Labor\_Hours_{gt}} \tag{2.2}$$

PCM refers to the product of *Defect Points* (in hours) and *Penalty Rate* as the *Defect Penalty*. This quantity is the basis of PCM's measure of quality in the LINE sample. Recall that PCM only measures quality in these specific parts of the manufacturing process. Importantly, the sampling rule to detect quality defects does not vary significantly across products, production lines, or work stations. *Quality*, then, is the ratio of *Defect Penalty* to *Standard Labor Hours*. To ensure that *Quality* increases when fewer defects are detected, we multiply this ratio by minus one.

$$Quality_{it}^{L} = -1 * \frac{Defect\_Penalty_{it}}{Standard\_Labor\_Hours_{it}} \tag{3}$$

3.3.5. Measures of Experience and Learning

Workers can improve *Efficiency* as well as *Quality* by learning from their own experience or by learning from the experience of working with others (Reagans et al. 2005; Mas and Moretti 2009). Individual experience (*iTENURE*) is measured as the number of months a given worker has been employed by the firm. Measuring the experience of working together with others (*gTENURE*) involves somewhat more subtlety. Group members tend to form subgroups along the lines of shared (demographic) characteristics within the overall group (Gibson and Vermeulen 2003; Lau and Murnighan 2005). At PCM, the worker's hometown is one of their most salient characteristics. We construct our measure of how long group members have been working together based on hometown-subgroups. The key justification for this choice is that coordination and communication are much easier within a subgroup than between subgroups; it is, however, the exposure to the different expertise of the other subgroup that determines learning. Therefore, learning from others will depend on how long members of one subgroup have had the opportunity to work together with other subgroups—i.e., it is the overlap between the experiences of the subgroups comprising a group that matters. We measure *gTENURE* by first identifying the most experienced worker in each subgroup (the "subgroup representative"). We then compute the minimum tenure across these subgroup representatives as this will give us a measure of the time that the subgroups have been able to work together.

We measure learning by assessing how *Efficiency* and *Quality* change in relation to these two experience measures.

3.3.6. Data

The data used for this study are proprietary and provided by PCM. We obtain data on (1) monthly performance for each group (in the GROUP sample) and for each individual (in the LINE sample), (2) monthly salary and bonus at the individual level, (3) employee characteristics, including tenure, gender, education level, hometown, and the referral status. These data are available from 2007 to 2009. We have 1,530 unique employees in the LINE sample; 1,334 of these individuals started their employment contract in the sample period (i.e., 2007-09). In the GROUP sample, we have data on 340 new employees out of 390 unique individuals.

LINE Sample Characteristics

Table 2 provides summary statistics on the employees in the LINE sample. The proportion of male employees is 0.57. These individuals have enjoyed on average some years of high school education (the corresponding mean value on EDUCA is 2.34, or the equivalent of junior high school). The monthly bonus is on average ¥136.71. Bonus payments vary considerably, however. The standard deviation is 178.51 and monthly payments range between −¥428.13 and ¥1,493.80. Note that bonus payments will be negative whenever the actual labor hours spent on a task exceed the standard labor allowed. In addition, PCM imposes a (quality) penalty for defective output. The dispersion in bonus payments reflects corresponding differences between employees in *Efficiency* and *Quality*. Indeed, while mean and median *Efficiency* are about 1.2, some workers complete their task 10 times faster than the standard labor hours available. Similarly, some workers are able to complete their job without quality defects (corresponding to the maximum value of *Quality*), while others incur a substantial penalty for faulty work.

<Insert Table 2 here>

The summary statistic of tenure is limited to new employees. The maximum tenure observed per new employee ranges between 1 and 34 months, with a median of 5 months.[24] The average maximum tenure is longer for those employees who have been referred by coworkers (mean=7.1 months) than for those who have been recruited into the firm on their own accord (mean=6.05 months). The correlation between *Efficiency* (*Quality*) and individual experience (i.e., *iTENURE*) is positive and significant (corr.=0.37, p<0.01 and corr.=0.17, p<0.01, respectively). These correlations are consistent with the idea that employees learn to become more efficient and to avoid defects over time.

Measured separately for each production line, hometown homogeneity is on average 0.23, but some groups are completely homogenous (*SAMEHOME* =1.00).

GROUP Sample Characteristics

[24] Including all workers in the analysis, this summary statistic has the maximum value 94 months.

Turning to the group production environment, the proportion of women is (1−0.24=) 0.76. The average level of education is roughly equivalent to junior high school (mean value of EDUCA=2.26). The average monthly bonus payment is about ¥118.10, but payments vary significantly. The sample minimum (maximum) bonus payment is −¥518.86 (¥473.14). Recall that PCM does not measure quality in the group production environment. Negative bonuses, therefore, are the result of groups needing longer to complete their tasks than standards allow.

<Insert Table 3 here>

As performance is only measured at the group level, we do not have summary statistics on *Efficiency* for the individual group members. Panel C of Table 3, however, reports that group-level *Efficiency* ranges between 0.54 and 4.63, and is on average 1.28, suggesting that groups tend to complete their activities within the allotted time. Group-level tenure (*gTENURE*) is not significantly associated with group-level *Efficiency*, suggesting that on average no learning from others in the group takes place.

The median maximum tenure observed per new employee is 4.5 months for non-referred workers and 7 months for referred workers. The hometown homogeneity index varies substantially across groups, and ranges between the values of 0.12 and 1.00.

3.4. Empirical Models and Results

The empirical predictions on how workforce homogeneity affects employee learning and their provision of effort depend on the joint specifics of the production environment and the incentive contracts. Consequently, we introduce our empirical analyses for each of our two samples (LINE and GROUP) separately. We examine the LINE production environment in Section 3.4.1 and the GROUP environment in Section 3.4.2.

3.4.1. LINE Sample: Empirical Models and Findings

In the LINE sample, we investigate the effect of workforce homogeneity on individual learning, so the unit of analysis is individual-calendar month. Both performance dimensions (i.e., *Efficiency*^{L} and *Quality*^{L}) measured at the individual level reflect learning outcomes, but we are particularly interested in *Quality*. As the LINE production environment suggests, learning about quality varies with information environment of the production line. The information environment is determined by *all* the workers on the production line. Hence, the workforce homogeneity (*HMGN*) is measured at the "group" level with two proxies, hometown homogeneity (*SAMEHOME*) and the fraction of referred workers (*RFLratio*). We specify the empirical model with the theoretical construct of workforce homogeneity denoted by *HMGN*, but we conduct the analyses with two abovementioned empirical proxies. We specify our models for the LINE sample as follows:

$$Quality^{L}_{i,t+1} = \alpha_0 + \alpha_1\, iTENURE_{it} + \alpha_2 HMGN_{gt} + \alpha_3\, HMGN_{gt} * iTENURE_{it} + CONTROL\ variables + \varepsilon_{it}\,, \quad (4.1)$$

$$Efficiency^{L}_{i,t+1} = \beta_0 + \beta_1\, iTENURE_{it} + \beta_2 HMGN_{gt} + \beta_3\, HMGN_{gt} * iTENURE_{it} + CONTROL\ variables + \varepsilon_{it}\,, \quad (4.2)$$

where subscript *i* represents individual, and *t* the calendar month, respectively. Models (4.1) and (4.2) are estimated at the individual level by individual fixed effect OLS regressions with robust standard errors. Employees' ability is the most important individual heterogeneity complicating performance (i.e., *Quality*^{L} and *Efficiency*^{L}). Including individual fixed effects controls for time-invariant unobservable heterogeneity and deals with the concern about ability differences among individuals. To examine learning effects, it is important to capture each individual's complete "learning profile". We accomplish this by using the sample of new employees who enter the firm during the sample period (2007-2009) (Shaw and Lazear 2008;

Seru et al. 2010).[25] We include as control variables other group characteristics, including the number of workers on the same production line (*SIZE*), average education level (*AVG_EDUCA*), average tenure (*AVG_TENURE*), and the fraction of male workers (*AVG_GENDER*). Year and production line fixed effects are also included.

We expect that employees accumulate their knowledge via their own experience (*iTENURE*) and hence demonstrate better performance on $Quality^L$ and $Efficiency^L$ over time (i.e., $\alpha_1 > 0$ *and* $\beta_1 > 0$). We model the effect of tenure on performance as a linear-log function, so we use the logarithm of *iTENURE* in our models. We predict that individual learning about quality is a negative function of homogeneity of a workforce on a given production line. Hence, we include the interaction term between *HMGN* and *iTENURE* in Models (4.1) and (4.2), but only expect the coefficient in model (4.1) to be negative (i.e., $\alpha_3 < 0$).

The results of Models (4.1) and (4.2) are presented in Table 4, and we discuss the results separately. Panel A of Table 4 shows that individual experience (*iTENURE*) is positively associated with $Quality^L$ across all specifications. We expect that workforce homogeneity decreases learning about quality. We present empirical results with two different homogeneity proxies, *SAMEHOME* and *RFLratio*, respectively. We do not find a significant coefficient for the interaction term between *SAMEHOME* and *iTENURE* in column (3), but column (5) shows a significantly negative coefficient for the interaction term between *RFLratio* and *iTENURE*, indicating that the fraction of referred workers decreases the extent to which employees improve production efficiency over time (−0.135, $p<0.05$). This finding is consistent with H1a that workforce homogeneity is negatively associated with individual learning about quality.

<Insert Panel A of Table 4 here>

[25] Otherwise, the estimation will be biased by the left-censored observations. That is, we exclude those workers who entered the firms before 2007 when investigating the learning effects for the LINE sample.

Similarly, Panel B of Table 4 presents robust positive coefficients for *iTENURE*, consistent with the idea that workers improve their efficiency by accumulating more individual experience. We do not expect that workforce homogeneity affects learning about efficiency in the LINE setting. Consistent with this prediction of H1b, we do not find significant coefficients for the interaction terms between *SAMEHOME* and *iTENURE* in column (3) and between *RFLratio* and *iTENURE* in column (5). The empirical evidence indicates that workforce homogeneity is not associated with individual learning about efficiency.

<Insert Panel B of Table 4 here>

In sum, we find that employees improve the production quality and efficiency by accumulating individual experiences. However, employees on the production line made up with a more homogeneous workforce (when measured using referral ratio) improve their production quality to a lesser extent than employees working with fewer referred workers around them.

Our current set of analyses cannot distinguish between learning and sample attrition explanations for our results (Seru et al. 2010). In addition to learning about quality and/or efficiency, employees become over time better able to assess their “fit” with the firm, their assigned tasks, and their collaboration with coworkers. As employees learn about whether they are a good match to the job, increased sorting is expected, with those who do not fit the work well expected to leave the firm. We plan to further explore the effect of sample attrition (or employee “learning about fit” in subsequent version of this paper). For now, we only highlight that our findings can be explained by both learning on the job and by mismatched employees leaving the firm.

3.4.2. GROUP Sample: Empirical Models and Findings

In the GROUP sample, the unit of analysis is group calendar-month and all variables are measured at the group level. Accordingly, we use group performance (i.e., $Efficiency^G$) as the dependent variable, which captures the outcome of effort provision and learning. The variable of interest is workforce homogeneity (*HMGN*), which is measured as either hometown homogeneity (*SAMEHOME*) or the referral ratio (*RFLratio*). We specify our model as follows:

$$\begin{aligned} Efficiency^G_{g,t+1} = \quad & \gamma_0 + \gamma_1 SIZE_{gt} + \gamma_2 gTENURE_g + \gamma_3\, HMGN_{gt} + \gamma_4\, HMGN_{gt} * SIZE_{gt} \\ & + \gamma_5 HMGN_{gt} * gTENURE_{gt} + CONTROL\ variables + \varepsilon_{gt}\ , \qquad (5) \end{aligned}$$

where subscript *g* represents each group, and *t* the calendar month, respectively. Model (5) is estimated at the group level by pooled OLS regressions with robust standard errors clustered by group. We include as control variables group characteristics, including average education level (*AVG_EDUCA*), dispersion of education level (*STD_EDUCA*), dispersion of tenure (*STD_TENURE*) and the fraction of male workers (*AVG_GENDER*). Group and year fixed effects are also included.

The free-rider problem of group incentive suggests a negative association between group size (*SIZE*) and $Efficiency^G$ (i.e., γ_1<0), as shirking is expected to be more frequent in a large group than in a small group. We expect that homogeneity of group members (*HMGN*) could mitigate the free-rider problem. Thus, we include the interaction term between *SIZE* and *HMGN* and predict the coefficient to be positive (i.e., $\gamma_4 > 0$).

The learning effect implies a positive association between group tenure (*gTENURE*) and $Efficiency^G$ (i.e., γ_2>0). When group members work together longer, they coordinate with each other more efficiently. We hypothesize that group learning increases in the degree of homogeneity of group members. Therefore, we predict the coefficient for the interaction term between *gTENURE* and *HMGN* to be positive (i.e., $\gamma_5 > 0$).

We test Model (5) with different proxies for *HMGN*, and present the empirical results using *SAMEHOME* or *RFLratio* as an empirical proxy in Panels A and B of Table 5, separately. We discuss the effect of workforce homogeneity on effort provision and learning about efficiency based on columns (5) in two panels of Table 5. With respect to the provision of employees' effort, we predict that workforce homogeneity (i.e., *SAMEHOME* or *RFLratio*) mitigates the free-riding problem. We do not find a significantly positive coefficient either for the interaction term between *SAMEHOME* and *SIZE* or between *RFLratio* and *SIZE*. This finding is inconsistent with our prediction of H2a that workforce homogeneity is positively associated with the provision of effort at the group-level.

<Insert Panels A and B of Table 5 here>

Turning to the learning effect (about efficiency), we expect that group homogeneity increases the positive association between *gTENURE* and $Efficiency^G$. The statistic significance of the simple effect of *gTENURE* depends on the proxy for *HMGN*. The results in column (5) of Panel A of Table 5 show a significantly negative simple effect of *gTENURE* (-0.239, $p<0.01$), but the coefficient is insignificant when the test is conducted with *RFLratio* (column (5) in Panel B of Table 5). Note that in a regression with interaction terms, the coefficient on the simple effect represents the partial effect of *gTENURE* on $Efficiency^G$ whilst holding *HMGN* (either *SAMEHOME* or *RFLratio*) constant at zero. The coefficients on the two separate interaction terms (i.e., *SAMEHOME***gTENURE* and *RFLratio***gTENURE*) are significantly positive (1.352, $p<0.01$ in Panel A; 0.617, $p<0.01$ in Panel B, respectively). Thus, the effect of *gTENURE* on $Efficiency^G$ depends on the magnitude of *HMGN*, which is either *SAMEHOME* or *RFLratio*).

To obtain some further insights on these relations, we compute the marginal effects of *gTENURE* across the range of practical values of *SAMEHOME* and *RFLratio*, separately. The value of SAMEHOME ranges from 0.12 to 1. The marginal effect of *gTENURE* is positive when *SAMEHOME* is between 0.2 to 1, and becomes statistically significant when *SAMEHOME* equals 0.4. The marginal effect of *gTENURE* turns positive when *RFLratio* is above 0.2 (out of the range from 0 to 0.5) and becomes statistically significant at *RFLratio*=0.45.

These findings suggest that whether a group of people can improve their efficiency through accumulating experience of working with their coworkers relies on group homogeneity. A working group with a high degree of heterogeneity encounters frictions in communicating and coordinating with coworkers, so the group performance may not even improve as the group tenure increases. Taken together, consistent with H2b, these findings demonstrate that the effects of workforce homogeneity on group learning about $Efficiency^G$ are not trivial.

3.5. Conclusion

A new literature on the significance of employee types on incentive outcomes is emerging (Oyer and Schaefer 2011; Lazear 1998; Ichniowski et al. 1997; Collins and Clark 2003; Bartling et al. 2012; Carlin and Gervais 2009). We build on recent work and in particular shed light on how workforce homogeneity interacts with the specific combination of incentive contracts and production environments. We document that the effect of workforce homogeneity differs between production environments along with different incentive contracts. The evidence offers insight on the interplay between workforce homogeneity and organizational designs. Workforce homogeneity is not exogenously determined.Our findings have implications for managers wishing to maximize the effectiveness of incentive contracts. Managers may attempt to influence the characteristics of the workforce by selecting hiring channels and by carefully using group dynamics to influence both the provision of effort and learning.

Indeed, the primary purpose of this study is to examine whether workforce homogeneity affects employee learning and the provison of effort. We study this question by exploiting three features of our research site: (1) the variety of hiring channels, (2) diverse workforce hometown, and (3) the presence of two production environments with associated incentive contracts. We document empirical evidence on the effects of the degree of workforce homogeneity on learning and effort.

Workers with similarity bear low costs in communicating and coordinating with each other. The low coordination costs bring either benefits or costs. In the LINE setting, we find that hometown homogeneity (measured by the fraction of referred workers) enables workers to collude to hide information and hinder production quality improvement across individual experience, but we do not find the same evidence when the homogeneity is proxied by hometown homogeneity. In the GROUP setting, our empirical evidence does not support the idea that workforce homogeneity creates strong mutual monitoring to mitigate the free-rider problem; meanwhile a working environment either with a high degree of hometown homogeneity or with a high fraction of referred workers indeed facilitates group learning about efficiency. In sum, we find workforce homogeneity plays a role in information sharing (i.e., learning effects) and this specific mechanism depends on the particular organizational design, which is the union of incentive contracts and production environments.

We derive our conclusion from field data of one particular manufacturing plant. However, we do recognize that management practices differ across firms, so we caution readers not to over generalize our empirical results. Despite the limitations, the most evident advantage of this field study is that it offers finely grained data in connection with the possibility for researchers to obtain an intimate understanding of the specifics of the production environment in which the workers interact in their day to day operations. As such, we attempt to open the black box on the question “how” employees’ characteristics matter beyond whether they matter.

3.6. References

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Appendix 1: Variable Descriptions

Variables	Description
Efficiency	=standard labor hours/actual labor hours
Quality	= -Defect penalty / standard labor hours
REFERRAL	=indicator variable, 1 if the worker is referred by an existing worker; 0 otherwise.
HMGN	=workforce homogeneity, measured either as hometown homogeneity (SAMEHOME) or the fraction of referred employees (RFLratio)
RFLratio	=the fraction of referral workers within a group =number of referral workers/ total number of workers
SAMEHOME	=hometown homogeneity of a group
SIZE	=the number of group members
iTENURE	=individual tenure
gTENURE	= group tenure, the overlap tenure among subgroups in the group =the minimum tenure among the maximum tenure of all subgroups
*RFLratio*SIZE*	=the interaction term between RFL_Ratio and SIZE
*SAMEHOME*SIZE*	=the interaction term between SAMEHOME and SIZE
*RFLratio*gTENURE*	=the interaction term between RFLratio and gTENURE
*SAMEHOME*gTENURE*	=the interaction term between SAMEHOME and gTENURE
*RFLratio*iTENURE*	=the interaction term between RFLratio and iTENURE
*SAMEHOME*iTENURE*	=the interaction term between SAMEHOME and iTENURE
STD_TENURE	=the standard deviation of individual tenure within a group
EDUCA	=Education level, ranges from 1 (primary school) to 5 (bachelor degree)
AVG_EDUCA	=the average of education level
STD_EDUCA	=the standard deviation of education level
GENDER	=dummy variable, 1 if the worker is male; 0 otherwise.
AVG_GENDER	=the fraction of male workers

Figure 1

Table 1 Employees' Hometown Distribution (by Province)

Province	Number of workers	(%)
Guangxi	399	20.78
Hunan	373	19.43
Henan	319	16.61
Hubei	149	7.7
Guangdong	137	7.14
Jiangxi	111	5.78
Sichuan	86	4.48
Guizhou	80	4.17
Shanxi	80	4.17
Gansu	78	4.06
Yunnan	41	2.14
Hainan	21	1.09
Anhui	20	1.04
Shandong	14	0.73
Fujian	5	0.26
Shanxi	4	0.21
Jiangsu	1	0.05
Hebei	1	0.05
Heilongjiang	1	0.05
Total	1,920	100

Table 2 Summary Statistics of the LINE Sample

Panel A: Individual Characteristics (N=7,319)

Variable	Mean	Std. Dev.	Minimum	Median	Maximum
$Efficiency^L$	1.26	0.49	0.00	1.20	10.04
$Quality^L$	-0.18	0.23	-3.00	-0.12	0.00
BONUS	136.71	178.51	-428.13	83.60	1493.80
GENDER	0.57	0.50	0.00	1.00	1.00
EDUCA	2.34	0.69	1.00	2.00	5.00

Panel B: Maximum Tenure per Each New Employee (in month)

Referral Status	N	Mean	Std. Dev.	Minimum	Median	Maximum
Non-Referral	1122	6.05	5.31	1.00	4.00	34.00
Referral	164	7.10	5.44	1.00	5.00	25.00

Panel C: Group (Production Line) Characteristics (N=375)

Variable	Mean	Std. Dev.	Minimum	Median	Maximum
$AVG\_Efficiency^L$	1.25	0.28	0.04	1.25	2.18
$AVG\_Quality^L$	-0.18	0.12	-0.83	-0.16	0.00
SIZE	19.52	9.00	1.00	19.00	47.00
RFLratio	0.12	0.14	0.00	0.08	1.00
SAMEHOME	0.23	0.12	0.11	0.19	1.00
AVG_TENURE	9.36	5.99	1.00	8.47	41.52
STD_TENURE	5.80	4.39	0.00	4.91	23.47
AVG_EDUCA	2.34	0.21	2.00	2.33	3.25
STD_EDUCA	0.65	0.22	0.00	0.68	1.41
AVG_GENDER	0.59	0.22	0.00	0.58	1.00

Panel D: Pearson Correlation Table (*P*-values are in parentheses.)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)
(a)$Efficiency^L$	1									
(b)$Quality^L$	0.12 (0.00)	1								
(c)iTENURE	0.37 (0.00)	0.17 (0.00)	1							
(d)EDUCA	-0.07 (0.00)	-0.06 (0.00)	-0.07 (0.00)	1						
(e)GENDER	-0.04 (0.00)	-0.20 (0.00)	-0.11 (0.00)	0.21 (0.00)	1					
(f)REFERRAL	0.03 (0.02)	0.02 (0.14)	-0.09 (0.00)	-0.06 (0.00)	-0.03 (0.01)	1				
(g)SAMEHOME	-0.02 (0.10)	0.14 (0.00)	0.18 (0.00)	-0.03 (0.03)	0.00 (0.87)	-0.03 (0.00)	1			
(h)AVG_TENURE	0.30 (0.00)	0.19 (0.00)	0.64 (0.00)	-0.11 (0.00)	-0.17 (0.00)	0.01 (0.32)	0.28 (0.00)	1		
(i)AVG_EDUCA	-0.22 (0.00)	-0.05 (0.00)	-0.28 (0.00)	0.26 (0.00)	0.12 (0.00)	-0.01 (0.51)	-0.10 (0.00)	-0.44 (0.00)	1	
(j)AVG_GENDER	-0.16 (0.00)	-0.09 (0.00)	-0.29 (0.00)	0.08 (0.00)	0.39 (0.00)	-0.06 (0.00)	0.00 (0.68)	-0.44 (0.00)	0.31 (0.00)	1

Table 3 Summary Statistics of the GROUP Sample

Panel A: Individual Characteristics (N=1,869)

Variable	Mean	Std. Dev.	Minimum	Median	Maximum
BONUS	118.10	132.72	-518.86	110.02	473.14
GENDER	0.24	0.42	0.00	0.00	1.00
EDUCA	2.26	0.65	1.00	2.00	5.00

Panel B: Maximum Tenure per Each New Employee (in month)

Referral status	N	Mean	Std. Dev.	Minimum	Median	Maximum
Non-Referral	286	6.10	4.66	1.00	4.50	34.00
Referral	54	7.13	4.56	1.00	7.00	21.00

Panel C: Group Characteristics (N=110)

Variable	Mean	Std. Dev.	Minimum	Median	Maximum
Efficiency^G	1.28	0.43	0.54	1.28	4.63
Quality^G	NA	NA	NA	NA	NA
RFLratio	0.14	0.12	0.00	0.14	0.50
SIZE	16.84	6.75	1.00	18.00	38.00
SAMEHOME	0.25	0.12	0.12	0.22	1.00
gTENURE	1.14	0.79	0.00	1.10	3.69
AVG_TENURE	1.65	0.51	0.46	1.63	3.74
STD_TENURE	0.70	0.26	0.00	0.69	1.53
AVG_EDUCA	2.25	0.15	1.67	2.26	2.67
STD_EDUCA	0.61	0.22	0.00	0.63	1.04
AVG_GENDER	0.26	0.16	0.00	0.26	0.67

Panel D: Pearson Correlation Table (*P*-values are in parentheses.)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)
(a)Efficiency^G	1									
(b)SIZE	-0.08 (0.39)	1								
(c)RFLratio	0.09 (0.36)	0.25 (0.01)	1							
(d)SAMEHOME	-0.18 (0.06)	-0.56 (0.00)	-0.01 (0.88)	1						
(e)gTENURE	0.13 (0.18)	-0.11 (0.23)	0.00 (0.99)	0.42 (0.00)	1					
(f)AVG_TENURE	0.24 (0.01)	-0.11 (0.26)	0.04 (0.68)	0.32 (0.00)	0.73 (0.00)	1				
(g)STD_TENURE	0.00 (0.97)	0.32 (0.00)	0.35 (0.00)	-0.21 (0.03)	-0.26 (0.01)	-0.15 (0.12)	1			
(h)AVG_EDUCA	0.18 (0.05)	0.20 (0.03)	0.10 (0.32)	-0.19 (0.05)	-0.01 (0.93)	-0.02 (0.86)	0.07 (0.47)	1		
(i)STD_EDUCA	0.11 (0.24)	0.29 (0.00)	0.04 (0.71)	-0.30 (0.00)	-0.14 (0.16)	-0.13 (0.19)	0.00 (0.97)	0.78 (0.00)	1	
(j)AVG_GENDER	0.03 (0.72)	-0.33 (0.00)	-0.24 (0.01)	0.10 (0.31)	-0.21 (0.02)	-0.13 (0.18)	-0.10 (0.29)	0.07 (0.44)	-0.04 (0.65)	1

Table 4 Learning Effects in the LINE Sample
Panel A: Learning about Quality

$$Quality^{L}_{i,t+1} = \alpha_0 + \alpha_1\, iTENURE_{it} + \alpha_2 HMGN_{gt} + \alpha_3\, HMGN_{gt} * iTENURE_{it} + CONTROL\ variables + \varepsilon_{it} \quad (4.1)$$

This model is estimated at the individual level by individual fixed effect regression. Robust standard error is reported in parenthesis. *,**,*** Indicate statistical significance at the 10% , 5% and 1% levels, respectively.

		$Quality^{L}$	$Quality^{L}$	$Quality^{L}$	$Quality^{L}$	$Quality^{L}$	$Quality^{L}$
		(1)	(2)	(3)	(4)	(5)	(6)
iTENURE	+	0.034***	0.034***	0.056***	0.034***	0.055***	0.077***
		(0.011)	(0.011)	(0.019)	(0.011)	(0.015)	(0.023)
SAMEHOME			-0.009	0.197			0.197
			(0.084)	(0.166)			(0.168)
SAMEHOME*iTENURE	−			-0.116			-0.116
				(0.074)			(0.075)
RFLratio					-0.025	0.242*	0.237*
					(0.043)	(0.138)	(0.139)
RFLratio*iTENURE	−					-0.135**	-0.135**
						(0.063)	(0.064)
SIZE		-0.012	-0.013	-0.013	-0.012	-0.011	-0.011
		(0.011)	(0.015)	(0.015)	(0.011)	(0.012)	(0.015)
AVG_TENURE		0.004**	0.004**	0.005**	0.004**	0.005**	0.005***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
AVG_EDUCA		0.090***	0.090***	0.087***	0.092***	0.090***	0.087***
		(0.033)	(0.033)	(0.034)	(0.034)	(0.034)	(0.034)
AVG_GENDER		-0.002	-0.002	-0.0004	-0.006	-0.013	-0.011
		(0.034)	(0.034)	(0.034)	(0.036)	(0.037)	(0.036)
Constant		-0.457***	-0.452***	-0.488***	-0.458***	-0.501***	-0.531***
		(0.095)	(0.109)	(0.111)	(0.095)	(0.102)	(0.120)
Observations		5,857	5,857	5,857	5,857	5,857	5,857
Number of individuals		1,334	1,334	1,334	1,334	1,334	1,334
Individual fixed effects		Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects		Yes	Yes	Yes	Yes	Yes	Yes
Production line fixed effects		Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared		0.442	0.442	0.442	0.442	0.443	0.443

Table 4 Learning Effect in the LINE Sample (continued)
Panel B: Learning about Efficiency

$$Efficiency^{L}_{i,t+1} = \beta_0 + \beta_1\ iTENURE_{it} + \beta_2 HMGN_{gt} + \beta_3\ HMGN_{gt}*iTENURE_{it} + CONTROL\ variables + \varepsilon_{it} \quad (4.2)$$

This model is estimated at the individual level by individual fixed effect regression. Robust standard error is reported in parenthesis. *,**,*** Indicate statistical significance at the 10% , 5% and 1% levels, respectively.

		$Efficiency^L$	$Efficiency^L$	$Efficiency^L$	$Efficiency^L$	$Efficiency^L$	$Efficiency^L$
		(1)	(2)	(3)	(4)	(5)	(6)
iTENURE	+	0.194***	0.194***	0.210***	0.194***	0.170***	0.186***
		(0.015)	(0.016)	(0.030)	(0.015)	(0.020)	(0.035)
SAMEHOME			-0.007	0.142			0.143
			(0.150)	(0.269)			(0.269)
SAMEHOME*iTENURE	NS			-0.084			-0.086
				(0.157)			(0.159)
RFLratio					-0.004	-0.319*	-0.323*
					(0.082)	(0.191)	(0.190)
RFLratio*iTENURE	NS					0.159	0.160
						(0.099)	(0.098)
SIZE		0.063***	0.063***	0.063***	0.063***	0.062***	0.061***
		(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.022)
AVG_TENURE		-0.002	-0.002	-0.002	-0.002	-0.0035	-0.003
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
AVG_EDUCA		-0.033	-0.033	-0.035	-0.033	-0.031	-0.033
		(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)
AVG_GENDER		-0.059	-0.059	-0.058	-0.060	-0.052	-0.051
		(0.041)	(0.041)	(0.042)	(0.043)	(0.043)	(0.044)
Constant		0.667***	0.671***	0.645***	0.667***	0.717***	0.696***
		(0.151)	(0.160)	(0.166)	(0.151)	(0.155)	(0.168)
Observations		5,857	5,857	5,857	5,857	5,857	5,857
Number of individuals		1,334	1,334	1,334	1,334	1,334	1,334
Individual fixed effects		Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects		Yes	Yes	Yes	Yes	Yes	Yes
Production line fixed effects		Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared		0.650	0.650	0.650	0.650	0.651	0.650

Table 5 Effort and Learning Effects in the GROUP Sample
Panel A: The Effect of Hometown Homogeneity (*SAMEHOME*)

$$Efficiency^{G}_{g,t+1} = \gamma_0+\gamma_1 SIZE_{gt}+\gamma_2 gTENURE_g+\gamma_3\, HMGN_{gt} +\gamma_4\, HMGN_{gt}*\, SIZE_{gt} +\gamma_5 HMGN_{gt} *\, gTENURE_{gt} +Control\ variables+ \varepsilon_{gt} \quad (5)$$

This model is estimated at the group level by pooled OLS regression. Robust standard error is clustered at the group level and reported in parenthesis. *,**,*** Indicate statistical significance at the 10% , 5% and 1% levels, respectively.

		$Efficiency^G$ (1)	$Efficiency^G$ (2)	$Efficiency^G$ (3)	$Efficiency^G$ (4)	$Efficiency^G$ (5)
SIZE	–	-0.018*	-0.024**	-0.025	-0.029***	-0.039
		(0.008)	(0.009)	(0.018)	(0.009)	(0.027)
gTENURE	+	0.008	0.067	0.068	-0.223**	-0.239**
		(0.060)	(0.089)	(0.093)	(0.080)	(0.101)
SAMEHOME			-1.258*	-1.311	-4.016**	-4.677*
			(0.684)	(1.045)	(1.508)	(2.566)
SAMEHOME*SIZE	+			0.005		0.047
				(0.048)		(0.081)
SAMEHOME*gTENURE	+				1.258**	1.352**
					(0.413)	(0.558)
AVG_TENURE		0.227**	0.201*	0.200*	0.038	0.016
		(0.089)	(0.101)	(0.102)	(0.099)	(0.110)
STD_TENURE		0.099	0.119	0.118	-0.059	-0.074
		(0.080)	(0.085)	(0.086)	(0.070)	(0.080)
AVG_EDUCA		1.106	0.987	0.993	0.951	0.993
		(0.723)	(0.775)	(0.812)	(0.769)	(0.847)
STD_EDUCA		-0.011	-0.027	-0.032	-0.043	-0.093
		(0.424)	(0.450)	(0.474)	(0.457)	(0.514)
AVG_GENDER		-0.942***	-0.665*	-0.663*	-0.609*	-0.584
		(0.249)	(0.306)	(0.311)	(0.332)	(0.334)
Constant		-0.763	-0.214	-0.214	1.003	1.100
		(1.307)	(1.315)	(1.328)	(1.335)	(1.369)
Observations		110	110	110	110	110
Group fixed effects		Yes	Yes	Yes	Yes	Yes
Year fixed effects		Yes	Yes	Yes	Yes	Yes
Adjusted R-squared		0.205	0.230	0.222	0.261	0.256

Table 5 Effort and Learning Effects in the GROUP Sample (continued)
Panel B: The Effect of Referral Ratio (*RFLratio*)

$$Efficiency^{G}_{g,t+1} = \gamma_0+\gamma_1 SIZE_{gt}+\gamma_2 gTENURE_g+\gamma_3\, HMGN_{gt}\ +\gamma_4\, HMGN_{gt}*SIZE_{gt} +\gamma_5 HMGN_{gt} * gTENURE_{gt} + Control\ variables + \varepsilon_{gt} \quad (5)$$

This model is estimated at the group level by pooled OLS regression. Robust standard error is clustered at the group level and reported in parenthesis. *,**,*** Indicate statistical significance at the 10% , 5% and 1% levels, respectively.

		$Efficiency^G$ (1)	$Efficiency^G$ (2)	$Efficiency^G$ (3)	$Efficiency^G$ (4)	$Efficiency^G$ (5)
SIZE	−	-0.018*	-0.018*	-0.025	-0.017*	-0.028
		(0.008)	(0.008)	(0.014)	(0.008)	(0.016)
gTENURE	+	0.008	0.013	0.022	-0.078	-0.098
		(0.060)	(0.06)	(0.065)	(0.072)	(0.056)
RFLratio			-0.224	-0.852	-0.748	-2.037**
			(0.491)	(0.574)	(0.631)	(0.860)
RFLratio*SIZE	+			0.0405		0.070
				(0.035)		(0.052)
RFLratio*gTENURE	+				0.448**	0.617***
					(0.159)	(0.171)
AVG_TENURE		0.227**	0.215*	0.213*	0.260**	0.274***
		(0.089)	(0.101)	(0.103)	(0.090)	(0.086)
STD_TENURE		0.099	0.108	0.154	0.128	0.215*
		(0.080)	(0.095)	(0.102)	(0.097)	(0.099)
AVG_EDUCA		1.106	1.097	1.023	1.113	0.990
		(0.723)	(0.706)	(0.681)	(0.700)	(0.659)
STD_EDUCA		-0.011	0.000	0.005	-0.018	-0.016
		(0.424)	(0.420)	(0.426)	(0.420)	(0.426)
AVG_GENDER		-0.942***	-0.951***	-0.896***	-0.888***	-0.769**
		(0.249)	(0.229)	(0.253)	(0.224)	(0.268)
Constant		-0.763	-0.715	-0.515	-0.780	-0.456
		(1.307)	(1.319)	(1.279)	(1.294)	(1.236)
Observations		110	110	110	110	110
Group fixed effects		Yes	Yes	Yes	Yes	Yes
Year fixed effects		Yes	Yes	Yes	Yes	Yes
Adjusted R-squared		0.205	0.198	0.193	0.200	0.204

Chapter 4

The Role of Reporting Uncertainty in Information Communication: Empirical Evidence on Loan Approval Decisions

Chapter 4: The Role of Reporting Uncertainty in Information Communication: Empirical Evidence on Loan Approval Decisions

4.1. Introduction

Decision rights and information do not always reside in the same party (Aghion and Tirole 1997; Baker et al. 1999; Bolton and Scharfstein 1998). When the information in question is not verifiable, this separation gives rise to "uncertainty" among decision makers (DMs) about the quality of the information being reported by information providers (IPs). The quality of reporting is determined by (1) the IPs' reporting objectives or (2) the IPs' reporting patterns or styles. The DMs' uncertainty about reporting quality is thus particularly prevalent when they are unfamiliar with the IPs. Specifically, "reporting uncertainty" is defined as the extent to which DMs are able to form an expectation about the quality (e.g., informativeness) of the information received and hence decreases as their familiarity with the IPs increases.[26] This uncertainty affects not only how DMs use the information, but also how the IPs report it. This study examines the role of reporting uncertainty in the information communication between DMs and IPs.[27]

I used data on used-car loan applications from a car dealership in Taiwan (referred to as CAR) to empirically examine this issue. CAR runs its used-car loan business through two business channels: franchisees and company-owned outlets. There are three parties involved in the application process, namely, borrowers, salespeople, and loan officers. All of the loan officers are employed by CAR, but the salespeople work at two different business channels.

[26] One example of such uncertainty is when two different IPs have the same information and report it in the same way, but the DM has different levels of understanding with the two IPs and hence interprets the same information from the two IPs differently.

[27] This idea is also termed "ambiguity" or "Knightian uncertainty" (Neamtiu et al. 2014; Williams in press). DMs' reporting uncertainty in this study relates to their knowledge rather than to the nature of the information. Therefore, I use the term "uncertainty" rather than "ambiguity" to stress the DMs' views of the quality of the information.

This study focuses on the information communication between the salespeople (i.e., the IPs) and loan officers (i.e., the DMs). The loan officers' working relationships with the salespeople are shaped by organizational structure: they may or may not be colleagues depending on whether the salespeople work at a company outlet or a franchise. Intuitively, loan officers are closer to the salespeople in outlets than to those at franchises, and they also have better knowledge about the former group's reporting objectives and styles.

In this setting, the interest rate of a loan ("loan rate") is an aggregate measure of the borrower's credit risk, as set by the salespeople, and it provides loan officers with additional information for their loan approval decisions. The loan rate represents a communication device, then, through which salespeople report a borrower's credit risk to loan officers.[28] The central argument of this study is that closer working relationships offer loan officers more knowledge in assessing the quality of the information being reported, and they thus experience less uncertainty when using information from company outlets to make decisions. Building on this, this study presents evidence on (1) how organizational structures affect the extent to which loan officers rely on loan rates to make loan approval decisions and (2) whether franchise salespeople set loan rates differently than salespeople working in company outlets.

Fischer and Verrecchia (2000) suggest that when the capital market is uncertain about a manager's reporting objectives, this uncertainty adds noise to the financial report and reduces the value relevance of the manager's report. However, as opposed to their predictions, empirical evidence in recent finance and accounting literature demonstrates that uncertainty results in behavioral biases in terms of processing the information (Williams in

[28] The loan rate in the loan approval setting is analogous to a financial report in capital markets, which is the communication device between firm management and investors.

press). People dislike uncertainty and exhibit uncertainty aversion in assuming the worst case: they take action to avoid the worst-case outcome (Epstein and Schneider 2008; Williams in press).

In a loan approval setting, loan officers are concerned about accepting bad loans. When they do not possess sufficient knowledge to assess the reporting quality of the loan rate as a credit risk measure, they impose a "belief" that the salespeople are unwilling to reflect the borrower's credit risk in the interest rates; in other words, that the salespeople are compressing the borrower's credit risk in setting the interest rate. This is the worst-case belief because it increases the likelihood of bad loans being approved. Moreover, this belief actually causes loan officers to view loan rates as being informative, because one unit of loan rate indicates a higher credit risk in cases where salespeople are reluctant to report a borrower's riskiness. Specifically, the bias arising from the worst-case belief is that loan officers view information (i.e., the loan rate) as being informative. Since the worst-case belief is associated with uncertainty about the reporting, loan officers will view franchisees' information as being more informative than company outlets' information. Hence, I predict that loan officers respond to franchisees' information more strongly than to outlets' information. I term this prediction the *decision bias hypothesis*.

At the other end of the spectrum, salespeople anticipate the loan officers' response to information of uncertain reporting quality (i.e., a higher likelihood of loan rejections) and take action to mitigate the adverse effects of decision biases. In their role as the loan rate setters, they assess the borrower's credit risk and determine the loan rate. Foreseeing that loan officers overvalue the level of risk embedded in the loan rates offered, salespeople will trend those rates downward to correct for decision bias in the information use. Since loan officers overvalue the borrower's credit risk to a greater extent when using information reported by franchisees versus that from company outlets, franchise salespeople are more prone to skew the loan rate downward than outlet salespeople. Therefore, I expect that loan rates submitted by franchisees to loan officers are lower than those submitted by company outlets. I term this the *reporting bias hypothesis*.

The empirical strategy for documenting the role of reporting uncertainty is to treat the information use and reporting in company outlets as a benchmark for analyzing whether these behaviors vary between the two business channels. In other words, the decision and reporting biases are measured in terms of "relative" magnitude instead of absolute scale. Note that these empirical tests rely on the premise that what differs between franchisees and outlets is the degree of loan officers' uncertainty about the quality of the salespeople's reporting. I discuss this issue in more detail in the section on the research setting (and in Section 4.4.4).

The empirical findings are consistent with the decision bias and reporting bias hypotheses. Specifically, I find that the negative association between loan officers' approval decisions and loan rates is stronger for franchise loans than for company outlet loans and that franchise salespeople set lower loan rates than those in outlets. An additional analysis of loan defaults captures the net effect of the combination of decision and reporting biases on loan performance. I find that the default rate is higher for franchise loans than for outlet loans. This particular finding not only corroborates the reporting bias hypothesis, but also suggests that the extent to which franchise salespeople skew the loan rate downward exceeds the magnitude of the loan officers' decision biases. This "excess" reporting bias by franchisees has a negative consequence: they face higher levels of loan defaults.

This study documents the role of reporting uncertainty in information communication within firms. Empirical evidence on the implications of uncertainty for information use is limited; the existing studies have been conducted in lab experiments or the capital market setting (Williams in press). Moreover, it is not clear how those findings apply to internal decision making, especially with regard to the sources of uncertainty. This study contributes to the literature on the information role of personal relationships. Prior studies suggest that personal relationships (e.g., school ties) that have been established based on common past experiences offer a channel for private information transfer and result in an information advantage (Brochet et al. 2013; Cohen and Frazzini 2008; Cohen et al. 2010).[29] This study, by contrast, highlights the effect of one specific type of personal relationship, as shaped by organizational structures, and documents how working relationships bias information processing.

In addition, the previous empirical studies that have investigated information use in decision making seem to take information supply as exogenously given.[30] This study sheds light on the interaction between the DMs and IPs in transferring information. This idea is not new. Prior literature on voluntary disclosure (Verrecchia 1983) or participative budgeting (Chow et al. 1988) has highlighted such strategic interactions with analytical models or lab evidence. However, I present instead empirical evidence from naturally occurring data on the effects of reporting uncertainty on information use and reporting simultaneously and argue that the anticipation of decision bias results in downward biases in setting loan rates. The evidence substantiates the general understanding of the interrelation between information use and information supply.

Previous studies on organizational structures have discussed the determinants of a firm's choice for franchised operations or company-owned outlets (Brickley and Dark 1987; Campbell et al. 2009; Lafontaine 1992; Martin 1988). The main determinants include

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[29] The role is trivial in this setting because information is aggregated and quantified to loan rates.
[30] Liberti and Mian (2009) focus on a setting where there are subjective and objective signals and investigate whether the hierarchical distance affects the extent to which decisions rely on different signals.

information asymmetry between headquarters and local units and the difficulty of monitoring local units. Taking this choice as exogenously given, this study finds that organizational structures shape people's mutual understanding (or working relationships) and are associated with biases in processing information. This study highlights the *ex post* costs associated with the choice of organizational structures.[31]

4.2. Hypothesis Development

4.2.1. Reporting Uncertainty and Organizational Structures

In a firm, the business is run through local units. Those units have information about local markets and customers that is important input for corporate decisions, and they occur in different organizational structures, depending on the way firms expand their businesses. Firms can expand by either franchising or running their own outlets (Martin 1988), so DMs receive information from either franchisees or company-owned outlets. Franchisees operate as independent organizations separate from the franchisor; outlets act as subordinate units under the parent company's control. The distinct organizational structures shape the levels of knowledge DMs have about the IPs in the local units. In the research setting for this study, CAR, in which franchisees and outlets co-exist side-by-side, loan officers have more knowledge about salespeople's objectives and behaviors in the company outlets than in the franchised operations for various reasons.

One important reason is associated with the varying degree of CAR's management control over the two business channels. CAR designs the incentive systems for salespeople in company outlets, so loan officers have sufficient knowledge about how salespeople in those outlets are rewarded. However, in the case of the franchisees, CAR only signs the franchise

[31] Several studies investigate the relationship between organizational form and information characteristics, for example, hard versus soft information (Stein 2002; Liberti and Mian 2009; Cerqueiro et al. 2011).

contract for listed services with the franchise owner and has little control over how they are operated. More importantly, loan officers have only limited knowledge about how salespeople are rewarded in franchisees, and this insufficient knowledge increases their uncertainty about the quality of the reporting, especially the reporting objectives.

In addition to the greater knowledge derived from company management control when dealing with outlets, loan officers' understanding of salespeople's reporting behavior benefits from closer proximity,[32] common language, and a shared culture determined by the firm's boundary (Grinblatt and Keloharju 2001). As applied to capital markets, one implication of proximity is that investors are more likely to invest in firms close to them because of their familiarity with those firms (so-called "home biases") (Coval and Moskowitz 1999). Extending that to this research setting, CAR is in closer organizational proximity to the company outlets than to the franchisees. That closer proximity creates advantageous conditions for personal interactions.[33] It is easier for people to sense others' styles through frequent face-to-face interactions than through impersonal contacts (e.g., emails). Loan officers have a more enhanced understanding of salespeople in outlets than of franchise salespeople.

Moreover, people within the same firm share a common language and the same culture (Crémer et al. 2007; Van den Steen 2010b). Language, no doubt, is the most important component in information communication for increasing mutual understanding. Each firm has specific "codes" (i.e., a common language) to facilitate coordination between agents (Arrow 1974); this specificity decreases communication costs within a firm but

[32] Proximity could be physical or organizational. In close approximation to the hierarchical distance in Liberti and Mian (2009), this study treats a firm's boundaries as a determinant of organizational distance.
[33] People within a firm meet each other in formal meetings and engage in social activities organized by the firm or individuals.

increases difficulty in communicating with an external party (Crémer et al. 2007; Weber and Camerer 2003).[34]

The assertion that corporate culture differs from firm to firm can be illustrated by the frequency with which mergers fail due to cultural conflicts (Van den Steen 2010a; Weber and Camerer 2003). Van den Steen (2010b) defines culture as shared beliefs and values, which implies fewer differences among individuals.[35] Specifically, people with shared beliefs follow a similar logic and have the same priorities in doing their work. The missions, strategies, and incentive structures of organizations are all part of their culture. Franchisees, as independent organizations, have their own objectives separate from those of the DMs, and that difference in objectives creates difficulties for the DMs in understanding IP behavior.

In sum, tighter management control, closer proximity, common language, and shared beliefs increase DMs' understanding about IPs in the same company. Note that the nature of loan officers' knowledge associated with working relationships may not be directly related to the parameter of interest (i.e., a borrower's credit risk in the setting) but refers to a general understanding about salespeople's reporting objectives and behaviors.

4.2.2. Reporting Uncertainty and Information Use

There are two different predictions about how DMs will respond to information when they are uncertain about the quality of the reporting. The first view treats reporting uncertainty as additional noise in the information processing (Fischer and Verrecchia 2000). Under that interpretation, DMs will view information of highly uncertain reporting quality as

[34] Weber and Camerer (2003) show that specific codes are developed over time and, more importantly, that these codes are only specific to a particular group and differ across groups, consistent with the notion of a common language within a firm. In a lab experiment, a pair of subjects (i.e., a manager and an employee) with the same set of pictures has to learn to jointly identify a subset of the entire set of pictures. To do this, they have to develop a common way of quickly describing the pictures so that the manager can direct the employee to pick up a pre-specified picture. In the beginning, the pair uses long expressions to describe the pre-specified picture. However, they shorten their expressions over time, and the employee learns to pick up the right picture sooner.

[35] People who work at the same firm have been hired under the same screening process and work under a standard employment policy. They have joint learning experiences, so shared beliefs emerge among them.

more noisy (less precise) than information of less uncertain reporting quality. This argument predicts that they will put less weight on the information coming from franchisees than on that reported by company outlets. This prediction is primarily supported by the analytical model in Fischer and Verrecchia (2000), but there are few empirical studies that document this view. Instead experimental and empirical evidence demonstrates people's biased response to uncertainty.

In one classic experiment, Ellsberg (1961)[36] demonstrated how people were averse to uncertainty (ambiguity). When they make judgmental decisions, such as assessing reporting quality, the degree of uncertainty aversion is driven primarily by the state of their general knowledge about the given subject (Fox and Tversky 1995; Heath and Tversky 1991).[37] The more people know, the less uncertain they feel. This suggests that DMs' knowledge about IPs increases their confidence in their own judgment regarding reporting quality and reduces their uncertainty aversion.

Uncertainty-averse DMs tend to maximize utility under a worst-case belief (Epstein and Schneider 2008). Put differently, DMs do not know whether the worst-case outcome will occur or not; however, they choose to believe that it will occur and take corresponding action to protect themselves.[38]

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[36] Ambiguity aversion can be illustrated by the classic experiment performed by Ellsberg (1961). In his two-urn experiment, Urn I has 50 red balls and 50 black ones; Urn II has 100 balls, but the ratio of red to black balls is unknown. Participants bet on the urn and the color of the ball jointly. A bet on Red_{I} means that the participant is choosing to draw a ball from Urn I and will receive a prize if the ball is red but no prize if it is black. Most people prefer to bet on Red_{I} rather than Red_{II} and Black_{I} rather than Black_{II}. Ellsberg claims that people feel uneasy about bets when they must guess at the odds. Since they are uncertain about the proportion of red to black balls in Urn II, they avoid betting on it. This is termed "ambiguity aversion." Caskey (2009) defines ambiguity aversion as a distaste for random outcomes that depend on an unknown probability distribution.

[37] Uncertainty aversion is triggered by contexts in which there is a contrast between states of knowledge, rather than by innate personal traits (Fox and Tversky 1995).

[38] Gilboa and Schmeidler (1989) explicitly model DMs' utility function as maximizing the minimum expected utility, which is called maxmin expected utility.

The definition of worst-case belief depends on the decision context. One manifestation in the capital market is investors' asymmetric reactions to good and bad news. With information that conveys good news, investors tend to be suspicious as to their payoff (i.e., a worst-case belief) and believe that the information is unreliable.[39] Therefore, they overreact to bad news, believing that it is precise, and underreact to good news, since they do not think good news can be precise. In sum, when DMs are uncertain about the quality of the information they receive, they choose to believe what is worse for their payoff.

In loan approval decisions, loan officers, by job design, are responsible for keeping default rates under control. In other words, their objective function is to minimize losses from loan defaults. They are therefore concerned about accepting bad loans. To a loan officer, the worst outcome is that a borrower turns out to truly be risky after the loan has been approved: such a case increases losses from loan defaults. That worst outcome is most likely to occur when salespeople are sluggish in increasing loan rates in response to a borrower's higher underlying credit risk. The reluctance (perceived or real) to reflect credit risk in the loan rate suggests that the changes in the borrower's underlying credit risk are larger than what the change in the loan rate would suggest. The worst-case belief about reporting quality in this setting is actually that the loan rate is informative. Hence, decisions are based to a larger extent on information of higher reporting uncertainty because of the worst-case belief that the reported credit risk measure is informative about the borrower's credit risk.

The uncertainty about reporting quality results in decision biases associated with the worst-case belief. Since loan officers are more uncertain about the reporting quality from

[39] I will borrow the exposition in Epstein and Schneider (2008) to make the idea concrete. Suppose that DMs want to know the parameter θ but only observe a signal $s = \theta + \epsilon$. The noise term is represented by $\epsilon \sim \mathrm{N}(0, \sigma_s^2)$, where $\sigma_s^2 \in [\underline{\sigma}_s^2, \overline{\sigma}_s^2]$. DMs do not know the probability over σ_s^2 but have a prior belief of its range. They choose their belief about the precision of the information from the range. When they observe good news, they choose the belief $\overline{\sigma}_s^2$. When receiving bad news, they choose the belief $\underline{\sigma}_s^2$ instead.

franchisees than from company outlets, they exhibit a higher degree of worst-case belief in interpreting franchise information than they do in using outlet information. Since the degree of a worst-case belief is associated with the perceived informativeness of the loan rate, loan officers' approval decisions are more strongly influenced by information submitted by franchisees than that supplied by outlets. I state the *decision bias hypothesis* as follows:

> **H1:** *Ceteris paribus*, the negative association between loan approval decisions and reported borrower credit risk is stronger for franchise loans than for company outlet loans.

4.2.3. Reporting Biases

I now turn to discussing how IPs report their information in response to the anticipation of DM bias. In the loan approval setting, salespeople provide the information (i.e., they are the IPs), and loan officers use that information to make decisions (i.e., they are the DMs). Their interaction occurs through the reporting of the information (i.e., the risk measure reported), which is similar to a financial report in capital markets, in which firm managers provide investors with financial information for investing decisions.

Loan officers are uncertain about the quality of the reporting, so they have a biased view about the informativeness of the reported risk measure and are less likely to approve loans in response to it. Anticipating this undesirable effect on loan approval probabilities, salespeople (especially those in franchises) try to mitigate the adverse consequences associated with reporting uncertainty. I argue that salespeople, anticipating loan officers' biases in using the information they provide, distort their reporting to offset the effect of decision bias.

The loan rate is the device that salespeople use to communicate a borrower's credit risk to loan officers. Decision biases occur when loan officers "overvalue" the level of risk contained in the loan rate, in the face of uncertainty about the reporting, when using that information to make their decision. Accordingly, salespeople will downplay the level of risk by skewing the loan rate downward. I will use an example to demonstrate how this anticipation works in a loan approval setting. Suppose the borrower's true level of credit risk is "medium" and the point at which loan officers decide to reject a loan is "high." If they were not worried about loan officers' decision biases regarding their reporting, salespeople would truthfully report the medium level of risk to loan officers. But since they know loan officers overvalue the level of risk reported, they are concerned that this borrower will be viewed as a high risk and the loan will be rejected. The salespeople therefore report a "low" level of risk to the loan officers, thereby demonstrating a "reporting bias." The loan officers overvalue the level of risk, as expected, and escalate the borrower's low level of risk to a medium level: however, they still accept the loan because the case remains below the point for loan rejections.

Anticipating the above situation, salespeople will trend a borrower's credit risk downward (e.g., from medium to low) when initially reporting information to offset loan officers' decision biases in overvaluing the level of risk. Since loan officers exhibit a higher degree of worst-case belief toward the risk measures reported by franchisees than toward those reported by company outlets, I predict that franchisees skew their risk measures downward to a greater extent than outlets. I state the *reporting bias hypothesis*, which concerns the salespeople's response to the effect of loan officers' uncertainty about the quality of reporting (which accordingly results in the anticipated decision bias), as follows:

> **H2:** *Ceteris paribus*, franchise salespeople underreport borrower credit risk to a greater extent than salespeople in company outlets do.

4.2.4. Biases and Decision Outcomes

In equilibrium, it is not clear whether reporting biases could perfectly offset decision biases or whether the two biases together actually affect decision outcomes. In many models of financial reporting, biasing activities do not affect the value relevance of the financial reporting (Verrecchia 1983). If DMs and IPs could fully anticipate the distribution of each other's biases, the two types of biases would cancel each other out on average and decision outcomes would still be efficient as a whole. These models assume that the users of the reports (1) develop rational expectations and (2) have perfect common knowledge about preparers' reporting objectives. Fischer and Verrecchia (2000) show that violations of the two assumptions affect the value relevance of information and ultimate decision outcomes.

This study examines the role of reporting uncertainty (i.e., uncertainty about the precision of reported information), which is exactly the violation of the second assumption. In this loan approval setting, the loan officers do not have perfect common knowledge about the IPs' reporting objectives and behaviors. This insufficient knowledge results in uncertainty aversion on their part, which leads to a biased view about a risk measure's informativeness. I predict that reporting uncertainty affects the ultimate outcome of approval decisions. In other words, the two types of biases are not perfectly offset. However, it is not clear *ex ante* whether decision biases or reporting biases are more dominant. Therefore, I do not develop any specific predictions about how reporting uncertainty affects decision outcomes through the two types of biases.

4.3. Research Design

4.3.1. Research Setting

The research site for this study is CAR, a car dealership in Taiwan. CAR has multiple businesses. It sells new cars of one particular make through its outlets and also offers used-car loans through two business channels: its own company outlets and franchisees.[40] The company has 964 salespeople working in 66 company-owned outlets, under 6 regional offices, and 346 franchise operations across Taiwan.[41] Figure 1 shows CAR's organizational structure. Loan officers work at either regional offices or headquarters. Headquarters, regional offices, and company outlets all fall under CAR's legal entity: franchise operations do not.[42] I rely on this feature as a proxy for the different degrees of DMs' reporting uncertainty. The separation between decision rights and information and distinctive coexistence of the two business channels make CAR's used-car loan business an appropriate setting for studying issues related to reporting uncertainty.

<Insert Figure 1 here>

Incentive Structures

CAR charges franchisees the capital charge rate (i.e., the cost of capital), and franchisees are the residual claimants of any remaining profit for loan rates above that rate. The capital charge rate is the same across applications within a given franchise operation but differs across franchisees. It varies based on a "franchisee rating" set by CAR in annual evaluations. Any losses associated with loan defaults (one of the evaluation items) downgrade a franchisee's rating and increase the capital charge rate they will be charged for the next period. Loan defaults thus do not affect franchisees' short-term monetary payoffs but do negatively impact future payoffs as a result of the downgraded rating, forcing them to pay

[40] The used-car market suffers from the adverse selection problem (Akerlof 1970). CAR offers franchisees particular services, such as quality checks and warranties, to reduce buyers' concerns about the quality of the used cars. CAR does not supply used cars to the franchisees and is not involved in incentivizing the selling of used cars. CAR's insufficient knowledge of how franchisees reward their salespeople might contribute to its uncertainty about their reporting.

[41] Untabulated descriptive statistics show that the median tenure for salespeople is 6 years, and the mean is 3.5 years; 82% of salespeople are male.

[42] Headquarters designs the franchise contracts and signs the contracts with franchisees. However, franchise operational activities are handled by CAR's company outlets and regional offices. For example, it is the salespeople in CAR outlets who collect the franchise loan applications to submit to loan officers.

higher capital charge rates to CAR. By contrast, at the company outlets, salespeople's bonuses increase in conjunction with the loan amounts approved, but not with the loan rates. Similarly, loan defaults do not directly affect salespeople's monthly bonuses, but will affect the year-end "employee rating," which is associated with future salary increases and promotion options.

Under the aforementioned incentive structures, both franchisees and outlets would like to communicate favorable information about a borrower's credit risk so as to get loan applications approved (for their own monetary benefit). At the same time, both types of organizations are penalized for withholding unfavorable information or distorting information, limiting salespeople's incentives for strategically manipulating information. More importantly, skewing the loan rate downward is costly for franchisees. It is not clear a priori whether both channels still have some incentives for manipulating information or there is a systematic difference in their incentives for misreporting borrowers' credit risk.

Although franchisees and company outlets differ on several dimensions with respect to the economic incentives for misreporting, those differences do not generate a clear prediction as to which channel's information is of poorer quality. In other words, despite the fact that incentive structures are designed to counteract salespeople's economic incentives for misreporting information, uncertainties still exist regarding the quality of the reporting. One salient difference between the two channels is the loan officers' degree of knowledge and confidence in assessing reports. As argued, loan officers are more uncertain about information from franchisees than from outlets.

For salespeople, setting the loan rate (i.e., the reporting information) is a difficult decision. Salespeople (especially those in franchisees) have an incentive to charge borrowers a higher loan rate in order to make a higher profit, but a higher loan rate will increase the likelihood of loan officers rejecting the application. This trade-off is more pronounced for franchisees than for outlets, because franchisees keep any profit above the capital charge rate. This trade-off is also an important factor contributing to loan officers' uncertainty about the quality of reporting from franchisees.

The loan officers' key responsibility is to analyze the profiles of loan applications and reject risky borrowers. Their bonuses decrease in the event of losses from defaults and increase in line with the loan amounts approved. They cannot be so strict as to reject good loans but have to be careful enough to reject bad loans. The fact of whether an application is from a franchisee or company outlet does not affect their bonus. The objective functions loan officers perform remain constant no matter where the loan originates.[43] In addition, loan officers' approval decisions are not based on an objective credit rating score model.

Essentially, their greatest concern is about accepting bad loans (i.e., Type II errors), while salespeople care much more about having good loans rejected (i.e., Type I errors), since the latter type of error decreases their short-term monetary payoff.[44] This conflict of interest between salespeople and loan officers is designed to minimize the total cost of the two errors combined (Sah and Stiglitz 1986) and does not vary between the two business channels. Although the objectives themselves are the same across the two business channels for both loan officers and salespeople, loan officers know more about how outlet salespeople deal with these conflicting objectives than they do about how franchise salespeople will.

Decision Process and Information Structure

[43] Rewarding loan officers based on loan profitability encourages them to accept risky loans to earn higher risk premiums. However, that is not what CAR expects loan officers to do. Therefore, the profitability of loans is not designed into their objective function.

[44] As mentioned, accepting bad loans also decreases salespeople's long-term payoffs through a lower employee or franchisee rating. This long-term incentive might mitigate the degree of conflict of interest between loan officers and salespeople.

There are two stages in the loan approval process and three parties (i.e., borrowers, salespeople, and loan officers) involved at different stages. In Stage 1, a salesperson settles on a loan rate with a borrower, and the borrower decides whether or not to apply for the loan. In Stage 2, the salesperson submits the application to a loan officer, who decides whether to accept or reject the application. The official approval process is the same for the two business channels.

This study focuses on the information communication between the salespeople and the loan officers: Stage 2 of the decision-making process. At Stage 1 of the process, there is an inherent information asymmetry about the borrower's credit risk between salespeople and borrowers. However, this asymmetry exists equally in both business channels, and there is no clear evidence that the problem is systematically different between the two channels. Since the empirical focus in this study is on a comparison of the two business channels, the issue of information asymmetry between salespeople and borrowers can be ignored.

The loan officers' ability to access information on the borrowers is the same for the two business channels. They have access to a database for checking a borrower's unusual transactions with other financial institutions, such as any overdue credit card payments.[45] In addition, they know the loan terms (e.g., loan rates and loan amount) and the borrower's personal information, as provided on application forms. They also receive additional documents on the borrower's credit risk.[46] One important aspect for loan officers is whether or not a borrower has a stable income, so salespeople will provide documents such as tax returns and salary slips to demonstrate financial status. Other information is also relevant but difficult to document. Some borrowers are self-employed or run small businesses, and there

[45] This database is maintained by the Joint Credit Information Center in Taiwan. It contains nationwide credit information and provides credit records to member institutions.
[46] Personal information includes name, gender, age, and residential addresses. Those items are standard requirements regardless of the business channel and not dictated by salespeople's choices.

are no official records about their income when transactions are done on a cash basis. Borrowers' personal lending conditions and credit reputations within the local neighborhood also play a critical role, but these variables, too, are difficult to confirm. Salespeople consider the relevant information in setting the loan rate. The loan interest rate is thus still informative, along with the other information available to the loan officers, in terms of the borrower's credit risk.

Ultimately, it is up to the loan officers to decide whether or not to accept the loan application. In the assessment process, they might raise some clarifying questions or ask for supplementary documents. However, it is not practically feasible for loan officers to adjust loan rates after salespeople have agreed to the terms with borrowers. Their decision rights are limited to approving or rejecting the loans.

4.3.2. Data

The dataset in this study covers all loan applications initiated in 2010 and 2011. It tracks the entire loan application process and includes applications that were withdrawn by borrowers in Stage 1 and rejected by loan officers in Stage 2. Data are available with respect to (1) loan characteristics, such as the loan amount (*Amount*), payment duration (*Term*), loan interest rates (*Rate*), and final outcome (*Default*); (2) observable decisions, including loan officers' approval decisions (*LoanAccept*) and borrowers' withdrawal decisions (*BorrWithdrawal*); and (3) salespeople's characteristics, including gender (*EmpGender*) and tenure (*EmpTenure*).

Salespeople's characteristics refer only to the characteristics of salespeople in company outlets, because the characteristics of franchise salespeople were not available to the car dealership (CAR) or to this study. The data limitations do not come from researcher's constraints. The most important data limitation is the unavailability of borrower characteristics that capture their credit risk. This limitation might affect the empirical tests for the reporting bias hypothesis, but not necessarily for the decision bias hypothesis. I discuss this further in Section 4.4.4.

I constructed three samples: the full, application, and approval samples. The sample construction is exhibited in Figure 2. The *full sample* includes all applications in Stage 1: that is all borrower applications, both those submitted and then withdrawn and those that were never withdrawn. The *application sample* (i.e., applications not withdrawn by the borrowers) includes all applications in Stage 2 that were either approved or rejected by loan officers. The full and application samples are used for primary empirical tests. Finally, an additional analysis of loan defaults is conducted with the *approval sample*, comprised of only approved loan applications, some of which ultimately went to default.

<Insert Figure 2 here>

The data was retrieved at the end of 2012, so not all loans have complete payment histories. Therefore, I construct a further sample that is limited to approved loans with complete payment histories.

All data are the outcomes in equilibrium. This study argues that it is the decision biases that drive reporting biases. However, the sequence of decision and reporting biases can never be directly tested with data observed in equilibrium. I rely on the institution background to evaluate the possibility of reversed sequence. Setting low interest rates might reduce the payoff for franchisees but does not necessarily affect company outlets. Therefore, *ex ante* I do not expect that franchisees have stronger economic incentive to set a lower loan rate than outlets. It is less likely that reporting biases occur before decision biases.

4.3.3. Variable Measurement

Measure of Information (Credit Risk) Reporting

Loan interest rates (*Rate*) represent the cost of credit risk. The higher the borrower's credit risk, the higher the loan rate. Although salespeople provide loan officers with several kinds of documentation (i.e., disaggregate information), the loan rate reflects aggregate information about the borrower's credit risk. Hence, loan officers take the loan rate as a measure of the borrower's credit risk and use this risk measure for their loan approval decisions. In other words, salespeople can influence loan officers' assessment of the borrower's credit risk by setting the loan rate. I take the loan rate (*Rate*) as a proxy for the information reported by the salespeople to the loan officers about a borrower's credit risk.

The loan interest rate is not a perfect proxy, however, since it includes a profitability element, namely the risk premium. Nonetheless, this level of noise is no different between the two business channels, so it is unlikely to affect the empirical inference. Moreover, since loan profitability is not included in the loan officers' incentive structure, the risk premium element probably does not interfere with the information about the borrower's credit risk.

The reporting bias hypothesis suggests that franchise salespeople are more reluctant to report a borrower's credit risk than outlet salespeople are, and thus keep loan rates low. With such reluctance at work, a borrower would have to carry a truly high level of risk for the salespeople to raise the loan rate. Accordingly, the level of risk included in a unit of loan rate is higher than would normally be expected. This suggests that the franchise loan rates are more informative about borrower's credit risk than company outlet rates. Note that it is the downward reporting bias in setting loan rates that increases the informativeness of the loan rates in terms of credit risk. Empirical evidence on the information content of loan rates could further validate the reporting bias hypothesis.

Measure of Decisions and Outcomes

Loan officers decide whether or not to approve a loan application: *LoanAccept* is an indicator variable indicating a loan officer's acceptance or rejection of a loan. Borrowers can also always withdraw their applications, and *BorrWithdrawal* is a binary variable identifying whether they have chosen to discontinue the loan process. The ultimate outcome of an approved loan is whether it is in default or not. *Default* is the corresponding indicator variable. For approved loans with complete payment histories, it indicates the occurrence of bad debt expenses. For approved loans without complete payment histories, *Default* refers to cases where a borrower has an overdue payment.

Measure of Uncertainty about Reporting Quality

Building on the argument that when loan officers have general knowledge about salespeople, it reduces their uncertainty about the quality of the reporting, I rely on the business channel (*fChannel*) through which the loan application arrives to measure the loan officers' uncertainty. Loan officers know whether a loan application has come from a franchisee or a company outlet. *fChannel* is an indicator variable distinguishing loan applications from franchisees (*fChannel*=1) from those submitted through outlets (*fChannel*=0).

Appendix 2 shows the geographic distribution of company outlets, as well as the number of loan applications per region from both business channels across counties in Taiwan. CAR has at least one outlet in each county, with the number of outlets in each region related to the size of the population. For example, there are multiple outlets in the two highly populated cities, Taipei and Kaohsiung, but only one in several less-populated counties. Since the demographics of each county may differ, I identify the geographic locations of franchisees and outlets, hoping to account for this heterogeneity by including "location" fixed effects.

While the specific location (i.e., address) of each company outlet could be identified, those of the franchisees were not available for this study. However, the franchise salespeople must submit their applications to salespeople in a specific outlet. In other words, there is a corresponding outlet salesperson for each franchise application. This allowed me to identify the relative location of the franchisees by determining which company outlet they were closest to. For the franchise operations, then, the location fixed effect is at the county level when there is only one company outlet and at a smaller district when there is more than one.

4.3.4. Descriptive Statistics

Tables 1 and 2 present summary statistics for the full sample and the application sample, respectively. There are 86,040 loan applications, of which 63% and 37% are from franchisees and company outlets, respectively. Both franchisees and outlets are substantial business channels. In the full sample, 15.7% of applications were withdrawn by the borrowers (Panel A, Table 1). Of the remaining applications, 86% were approved by loan officers (Panel A, Table 2). The average loan amount in the full sample was NT $284,740 (around US $9,500). The average annual loan rate (*Rate*) was 13.4%, with an average payment term of 2.6 years (Panel A, Table 1).

<Insert Table 1 and Table 2 here>

The summary statistics for the approval sample are reported in Table 3. The average default rate of the approval sample is 2%, which decreases to 1.2% in the sub-sample limited to approved loans with complete payment histories (Panel A, Table 3). Loans from franchisees exhibit a higher default rate than loans from company outlets in the entire approval sample, including both complete and incomplete payment histories (Panel B, Table 3). However, loans from franchisees show a lower default rate for the approval sample with only complete payment histories (Panel C, Table 3).

<Insert Table 3 here>

There are some differences in the borrower withdrawal rate and loan approval rate between franchisees and company outlets. Panel D of Table 1 shows that outlets (16.1%) have a higher borrower withdrawal rate than franchisees (15.5%). This result is consistent with what the reporting biases hypothesis would predict. Since franchisees set lower loan rates than outlets do, franchisee borrowers are less likely to withdraw their applications than outlet borrowers are. In Panel D of Table 2, the loan officers' approval rate is slightly higher for franchisees (86.3%) than for outlets (85.3%). On the whole, although franchisees have a lower borrower withdrawal rate and a higher approval rate than outlets, their default rate is higher for the entire approval sample (Panel B, Table 3).

No matter which sample is used for analysis, franchise loan rates are statistically lower than outlet loan rates. This finding is in line with the idea that franchise salespeople skew their loan rates downward to a greater extent than salespeople in company outlets. Furthermore, the interest rate for approved loans is lower for franchisees than for outlets (Panel B, Table 3). This suggests that at the same loan rate, loan officers are more likely to reject franchise loans than outlet loans, consistent with the result that the loans approved for franchisees have a lower loan rate on average.

As the Pearson correlation table shows (Table 4), the correlation between *Default* and *Rate* is positive and significant (corr. =0.09, p<0.01), and *Rate* is significantly and negatively correlated with *LoanAccept* (corr. = -0.17, p<0.01). These correlations are consistent with the idea that loan rates reflect a borrower's credit risk. Although the loan rate is a measure of the borrower's credit risk, it also contains salespeople's biases. One should be cautious in drawing any inference from the differences in the borrowers' "true" levels of risk between the two channels based on the loan rates observed. Given the lower loan rates for franchise loans, it would appear that franchisees have less risky loans. Yet, the higher default rate of those loans in the entire approval sample directly contradicts this inference.

<Insert Table 4 here>

4.4. Empirical Models and Results

I use the application and full samples to test the decision bias and reporting bias hypotheses, respectively. In addition, I conduct an analysis of the loan defaults to evaluate an alternative explanation for the results of the reporting bias hypothesis and examine the net effect of the two types of biases on loan outcomes (*Default*).

4.4.1. Decision Bias Hypothesis

I used the application sample to test whether the association between loan officers' approval decisions and the reported risk measure varies between franchisees and company outlets. I include *LoanAccept* as a dependent variable, which indicates whether the application is approved by a loan officer or not. Loan rate (*Rate*) is the proxy for a borrower's credit risk as reported by salespeople. I expect the association between *LoanAccept* and *Rate* to differ between the two channels (*fChannel*). To test the difference, I also include the business channel (*fChannel*) and the interaction term between *fChannel* and *Rate*. I specify the empirical model for the decision bias hypothesis as follows:

$$LoanAccept_i = \alpha_1 Rate_i + \alpha_2 fChannel_j + \alpha_3 Rate_i * fChannel_j + \Sigma\alpha_i Control_i + LocationFE_k + YearFE_t + \varepsilon_i, \quad (1)$$

where subscript *i* represents each loan application, *j* the business channel (i.e., franchisee or outlet), *k* the location that indexes the geographic district, and *t* the calendar year in which the salespeople filed the application.[47]

[47] Since it is a cross-sectional rather than panel dataset, there is no subscript *t* for each variable.

Model (1) is estimated at the loan application level using a linear probability model with standard errors clustered by salesperson.[48] Each loan application has only one observation in the dataset, but a single salesperson is likely to deal with multiple loan applications. Thus, the standard errors are clustered at the salesperson level. In addition to year fixed effects, location fixed effects are included to control for borrower preferences and the market competition specific to geographic districts.[49]

I include characteristics related to loan applications as additional control variables. Loan characteristics include the loan amount (*Amount*), payment term (*Term*), and borrower's gender (*BorrGender*). These loan characteristics also affect loan officers' evaluation of a loan applicant's level of risk.[50]

Since the loan rate represents the borrower's credit risk as priced by salespeople, loan officers use it as a risk measure in making loan approval decisions. The riskier the loan application, the less likely it is to be accepted by loan officers (i.e., $\alpha_1<0$). The decision bias emerges because of loan officers' uncertainty about the reporting quality of the loan rate as a risk measure. The decision bias hypothesis predicts that information from franchisees is subject to a greater degree of worst-case belief than information from company outlets. Loan officers are more likely to reject franchise applications than outlet applications when faced with an increase in the loan rate, because they view franchise loan rates as more informative than outlet rates. Hence, the empirical prediction would be that *LoanAccept* is more

[48] Since the coefficient for the interaction term of non-linear models might be misleading (Ai and Norton 2003), I report results estimated by a linear probability model as the primary tests. I also re-estimate the empirical model using logit regressions and test the difference in the average marginal effects of loan rates between the two channels as robustness checks. Detailed results are reported in Table 8.

[49] As mentioned, there are salespeople in company outlets who deal with franchise applications. I use that match to identify the corresponding outlets for franchisees.

[50] CAR only knows the characteristics for salespeople in its company outlets. Salespeople's characteristics include their gender (*EmpGender*) and tenure (*EmpTenure*). Therefore, the primary empirical model does not include salespeople's characteristics.

negatively sensitive to *Rate* for franchisees than for outlets (i.e., α_3<0). Table 5 presents the results of Model (1).

<Insert Table 5 here>

Column (3) of Table 5 reports the results of the full model, which includes an interaction term. The main effect of *Rate* on *LoanAccept* indicates a negative association between loan approval decisions (*LoanAccept*) and borrower's credit risk (*Rate*) (-1.613, p<0.01) only for the outlet loan applications (*fChannel*=0). Given that the coefficient for the interaction term between *Rate* and *fChannel* is also significantly negative (-0.441, p<0.01), the negative association between *LoanAccept* and *Rate* also holds for franchise loan applications.[51] This negative coefficient for the interaction term (i.e., α_3) shows that in response to an increase in loan rates, loan officers are less likely to accept franchise applications than outlet applications, which is consistent with the prediction of H1 that *LoanAccept* is more negatively sensitive to *Rate* for franchise loans than for outlet loans.

This study investigates whether loan officers use franchisee information differently than outlet information, so it focuses on the *Rate* coefficient as a measure of how DMs respond to information. Another interesting issue to look at is whether there is a significant difference in the likelihood of loan acceptance between the two business channels. The coefficient for *fChannel* (i.e., α_2) is significantly positive (0.061, p<0.01). The combined findings suggest that when *Rate* is 13.83%, the likelihood of loan approval is the same between franchisees and company outlets. When *Rate* goes above or below 13.83%, franchise loans are either less or more likely to be approved, respectively, than outlet loans.

Columns (4) and (5) of Table 5 report results for franchisees and company outlets, respectively. This sub-sample analysis allows the coefficients for all variables to vary

[51] The untabulated F statistic (829.63) of the joint test (α_1+α_3=0) also supports this inference.

between the two channels and is used to validate the results in column (3). Consistent with the prediction, the coefficients on *Rate* are significantly negative for both franchisees and outlets (-2.034, $p<0.01$; -1.617, $p<0.01$, respectively). Also, as the decision bias hypothesis predicts, the magnitude of the coefficient on *Rate* is significantly larger for franchisees than for outlets ($\chi^2=20.00$, $p<0.01$). The separate analyses with applications from each channel are consistent with the results reported in column (3).

In sum, I find that loan approval decisions for franchises are more responsive to the information provided than those for outlets. This finding supports the idea that loan officers are more uncertain about the quality of the information from franchisees, so they make their approval decisions based on a belief that franchise risk measures are more informative and react more strongly to the information. Consistent with the decision bias hypothesis, the negative association between loan officers' approval decisions (*LoanAccept*) and the reported risk measure (*Rate*) is stronger for franchisees than for outlets.

4.4.2. Reporting Bias Hypothesis

The reporting bias hypothesis implies that given the same borrower, a salesperson in a franchise sets a lower loan rate than a salesperson in a company outlet does. I use the full sample to test whether the loan rates are significantly lower for franchise loans than for outlet loans. I include *Rate* as the dependent variable and *fChannel* as the main explanatory variable. The empirical model for the reporting bias hypothesis is summarized in Model (2).

$$Rate_i = \beta_1 \, fChannel_j + \Sigma \, \beta_i \, Control_i + LocationFE_k + YearFE_t + v_i \, , \qquad (2)$$

where subscript *i* represents each loan application, *j* the business channel (i.e., franchisee or outlet), *k* the location that indexes the geographic district, and *t* the calendar year in which salespeople filed the application.

Model (2) is estimated at the loan application level using OLS regressions with standard errors clustered by salesperson. Year and location fixed effects are both included. Since loan rates are also determined by other loan terms offered by salespeople and salespeople's abilities to evaluate credit risk, loan characteristics are also included in Model (2).

Importantly, the difference in borrower characteristics between the two channels might affect the empirical results. The location fixed effects control for borrower characteristics (e.g., wealth or education) specific to the geographical districts. I also control for the loan amount (*Amount*), which is associated with borrower preferences for the class and condition of used cars. These controls decrease the likelihood that this estimation is influenced by any systematic differences in borrower characteristics between the two channels.

I expect that, all other things being equal, franchisees trend loan rates downward to a greater extent than company outlets do (i.e., $\beta_1 < 0$). The main interest of the reporting bias hypothesis is whether salespeople, in anticipation of loan officers' decision biases, underreport borrowers' credit risk by setting lower loan rates. I use the full sample to assess whether franchise salespeople have a general tendency to set lower loan rates than outlet salespeople. The results of Model (2) are summarized in Table 6. Column (1) of Table 6 reports the results using the full sample, and the significantly negative coefficient for *fChannel* (-0.504, $p<0.01$) is consistent with the reporting bias hypothesis that franchise salespeople tend to set lower loan rates than those in outlets do.

<Insert Table 6 here>

However, not all loan applications in the full sample result in a loan being extended to a borrower (referred to here as an "executed" loan). Some applications are withdrawn by borrowers, and some are rejected by loan officers. Only those loans that are not withdrawn by borrowers and also approved by loan officers are actually executed. I conjecture that franchisees' tendency to lower a loan rate is weaker when they do not expect the loan to be executed. This conjecture predicts that the coefficient in *fChannel* (i.e., β_1) will differ between the executed and non-executed loans.

I split the full sample into executed and non-executed loans in two different ways. First, the full sample is split into "borrower non-withdrawal" and "borrower withdrawal" sub-samples, and the results of the sub-sample analyses are reported in columns (2) and (3), respectively. Second, results are shown for the loan applications that were accepted by both borrowers and loan officers, as well as the loan applications that were either withdrawn by borrowers or rejected by loan officers in columns (4) and (5), respectively.

Consistent with the results in column (1), the coefficients for *fChannel* are significantly negative across all sub-samples (i.e., executed and non-executed loans), suggesting that, in general, franchise salespeople have a stronger tendency to skew loan rates downward than salespeople in outlets do. What's more, the magnitude of the negative coefficient for *fChannel* is significantly larger for executed loans than for non-executed loans, regardless of how the executed or non-executed loans were characterized (χ^2=11.32, p<0.01; χ^2=18.16, p<0.01, respectively). This finding supports the conjecture that when franchise salespeople do not expect the loan to be executed, for whatever reason, there is less need to skew the loan rate to offset loan officers' decision biases.

The finding that franchise loans have lower loan rates than outlet loans might be driven by unobservable differences in the levels of borrower credit risk. It is possible that franchise borrowers are systematically less risky than outlet borrowers. However, the descriptive statistics of the entire approval sample show that the default rate is statistically higher for franchisees than for outlets. This statistic on loan defaults is inconsistent with that alternative explanation. Therefore, it is less likely that any fundamental difference in borrower credit risk between the two channels is driving the empirical findings. The formal test on loan defaults in the next section further corroborates the descriptive statistics on the default rate and discredits the idea that the levels of credit risk are lower for franchise borrowers than for outlet borrowers.

4.4.3. Outcome of Loans: Default

I conduct an additional analysis on loan defaults using the approval sample. This serves two purposes: (1) it offers additional evidence for salespeople's downward reporting bias in setting the loan rate; and (2) it assesses the net consequence of loan officers' decision biases and salespeople's reporting biases on loan outcomes.

Reporting Biases and Information Content

In addition to resulting in different loan rates between the two channels, the downward reporting bias affects the information content of those loan rates. When salespeople are reluctant to report a borrower's credit risk, they only slightly adjust the loan rate even though the borrower's credit risk warrants a more considerable adjustment. In other words, loan rates developed by franchisees contain more information about the borrower's credit risk than those set by outlets. To test the implication of reporting bias on the information content of loan rates, I include loan defaults (*Default*) as the dependent variable and *Rate* as the variable of interest. I am interested in seeing whether the information content of the loan rates differs between the two channels, so I include *fChannel* and the interaction term between *Rate* and *fChannel* in the specified Model (3).

$$Default_i = \gamma_1 Rate_i + \gamma_2 fChannel_j + \gamma_3 Rate_i * fChannel_j + \Sigma\gamma_i Control_i + LocationFE_k + YearFE_t + \delta_i , \quad (3)$$

where subscript *i* represents each loan application, *j* the business channel (i.e., franchisee or outlet), *k* the location that indexes the geographic district, and *t* the calendar year in which salespeople filed the application.

Model (3) is also estimated at the loan application level using a linear probability model with standard errors clustered by salesperson. Year and location fixed effects are both included; loan characteristics are also included in Model (3). As described, not all approved loans have complete payment histories. Panel A of Table 7 reports the results of Model (3) using the approval sample that includes approved loans having both complete and incomplete payment histories.

<Insert Panel A of Table 7 here>

Column (1) in Panel A of Table 7 reports the results with an interaction term, and columns (2) and (3) present the results for franchisees and company outlets, respectively. The two sets of results are consistent with each other. Column (1) reports significantly positive coefficients for both *Rate* (0.266, $p<0.01$) and the interaction term between *Rate* and *fChannel* (0.177, $p<0.01$). Columns (2) and (3) likewise show a positive association between *Default* and *Rate* for franchisees and outlets (0.447, $p<0.01$; 0.258, $p<0.01$, respectively). What's more, the coefficient for *Rate* is higher for franchisees than for outlets ($\chi^2=21.01$, $p<0.01$). These findings corroborate the idea that loan rates are a measure of the borrower's credit risk and also suggest that franchise loan rates contain more risk information than loan rates set by salespeople in outlets. This additional evidence supports the implication of the reporting bias hypothesis that franchisees are more reluctant to report credit risk and include more risk information in the same unit of loan rates than outlets.

Net Effects of the Decision and Reporting Biases

Another important question, besides determining whether there is an association between *Default* and *Rate*, is whether salespeople's biases in setting the loan rate offset loan officers' overvaluation of the level of risk contained in loan rates. In order to examine the net effect on loan outcomes, I estimate Model (3) excluding the interaction term between *Rate* and *fChannel*. Column (4) in Panel A of Table 7 presents the results of a linear probability model. The primary interest of this specification lies in whether the ultimate loan performance (i.e., Type II decision errors) differs between the two channels. The positive coefficient for *fChannel* (0.008, $p<0.01$) indicates that franchise loans have a higher default rate than outlet loans. This finding demonstrates that the reporting biases on the part of franchisees have a negative consequence: loan officers fail to reject the risky loans with underreported risk measures, and this leads to more defaults for the franchisees. It seems that the franchisees' downward reporting bias is greater in magnitude than the loan officers' decision bias and results in more decision errors (i.e., acceptance of bad loans).

I re-estimate Model (3) using only approved loans with complete histories as a robustness check: the results summarized in Panel B of Table 7 are qualitatively the same as the results using the entire approval sample (in Panel A of Table 7).

<Insert Panel B of Table 7 here>

I re-estimate Models (1) and (3) with a non-linear probability model (i.e., logit regressions) as a robustness check. The coefficients are reported in Panel A of Table 8. Based on these results, I compute the average marginal effects of loan rates on the probabilities of *LoanAccept* and *Default* for each channel, but test the "interaction effect" with the method proposed in Ai and Norton (2003).[52] The interaction effects documented in Panel B of Table

[52] Detailed explanations can be also found in Norton et al. (2004) and Karaca-Mandic et al. (2012).

8 are generally consistent with the coefficients of the interaction terms of the linear probability model reported in Tables 5 and 7.

<Insert Table 8 here>

4.4.4. Discussion

This study investigates the role of so-called reporting uncertainty in the interaction between loan officers and salespeople by examining the differences between two specific business channels with regard to (1) the relationship between loan approval decisions and loan rates and (2) loan rates. An obvious weakness in the empirical analyses is the lack of a direct measure of reporting uncertainty. The empirical tests rely on the premise that the business channels are subject to different degrees of reporting uncertainty and therefore serve as an appropriate proxy. I discuss whether other differences between the two channels could explain the documented findings.

Endogenous Choice for Franchisees and Company Outlets

Prior studies suggest that when information asymmetry between headquarters and local units is great and monitoring is problematic, firms tend to run their businesses through franchising, rather than establishing their own outlets (Campbell et al. 2009; Martin 1988). Information asymmetry and monitoring difficulty are associated with geographic distance. As the geographic distribution of loan applications in Appendix 2 shows, there is at least one company outlet and one franchise in each county. To account for this endogenous choice between franchisees and outlets, I include location fixed effects in all of the empirical tests. The location fixed effects control for the distance between headquarters and the local units and thus reduce concerns about differences in the initial information asymmetry and monitoring difficulties across all units.

Incentive Structures and Loan Approval Decisions

The incentive structures for franchisees and outlets suggest a difference in the extent to which CAR is compensated for accepting risky loans. As described, CAR is the residual claimant in the case of company outlets but not for franchisees. The direct implication is that CAR can be compensated with a higher loan rate for accepting risky outlet loans. When a risky borrower arrives at a company outlet, CAR, as the residual claimant, may bear a higher risk in providing the loan, but it also shares the profit generated by the attendant higher loan rate. The same is not true for deals struck by franchisees, however. CAR only charges them the capital charge rate, so its payoff is independent of the loan rates set for applications received through franchisees. In other words, CAR does not earn risk premiums for approving risky borrowers conducting business through the franchise operations. In that sense, loan officers are more willing to accept risky loans from outlets than they are to accept ones from franchisees. Accordingly, the extent to which CAR can be compensated for borrowers' level of risk might explain the difference in correlation between *LoanAccept* and *Rate* between the two channels.

In the current set of empirical analyses, the business channels coincide with the incentive structures, so I cannot discern whether the finding is driven by loan officers' uncertainty about the quality of reporting or the risk premiums argument presented above. In an attempt to parse out these two explanations, I analyze whether decision biases decrease in relation to salespeople's tenure by only using data from applications obtained from company outlets. Salespeople's tenure captures the variations in loan officers' reporting uncertainty within CAR. Following the same reasoning, I expect decision biases to decrease with tenure. The results are reported in Table 9. I sort salespeople into senior and junior groups based on the mean of *EmpTenure*. Indeed, I find that the negative relationship between *LoanAccept* and *Rate* is stronger for junior salespeople than for senior salespeople.

<Insert Table 9 here>

Salespeople's tenure might also reflect their ability to evaluate borrowers' levels of risk. However, I do not find a significant difference in the default rate between senior and junior salespeople. I take this finding as an indication that seniority on the part of salespeople does indeed impact loan officers' reporting uncertainty. Since all salespeople in CAR outlets are subject to the same incentive structure, this finding is consistent with the decision bias hypothesis that the association between loan officers' approval decisions and loan rates varies according to salespeople's seniority, a proxy for reporting uncertainty. In sum, I do not find direct evidence suggesting that it is the incentive structure rather than reporting uncertainty that explains the documented differences between the two channels.

Differences in Borrowers' Underlying Credit Risk

Data on borrower characteristics are not available for this study, so it is important to discuss whether there could be some unknown, systematic difference in the borrowers' underlying credit risk driving the empirical results. This systematic difference might emanate from self-selection on the borrowers' part or salespeople's preferences in terms of selecting borrowers. This data limitation poses a serious threat to the empirical test for the reporting bias hypothesis, since lower franchise loan rates might simply represent less risky borrowers. I exclude this possibility by showing that franchisees have a higher default rate than outlets.

In terms of testing the decision bias hypothesis, the data limitation is less of a concern. The primary interest of that hypothesis is the quality of the reporting, which concerns the way in which loan rates reflect a borrower's credit risk. Suppose that there were indeed some fundamental differences in borrowers' credit riskiness that were not captured by the researchers. As long as loan officers viewed a franchisee's reporting quality the same as an outlet's, they would not treat the information any differently. What matters is the loan officers' opinions about how salespeople reflect borrower credit risk in the loan rate, not the borrower's credit risk per se. In other words, differences in borrower credit risk are less likely to be a cause driving the difference in loan officers' responses to the information received.

4.5. Conclusion

The prevalence of information transmission in decision making comes from the separation of information supply and decision rights. Firms *ex ante* design mechanisms for inducing truthful reporting, but *ex post* evaluation of the quality of that reporting remain difficult for DMs, especially when they lack sufficient knowledge about the providers of information (IPs). The primary purpose of this study is to examine the effects of "reporting uncertainty" on both the use and the reporting of information. I use data on used-car loan applications from a car dealership in Taiwan (CAR) where (1) IPs work in either franchisees or company outlets and (2) available data on sequential decisions (i.e., loan rates, loan approval decisions, and loan defaults) allows for inferences about the interaction between DMs and IPs. I rely on working relationships shaped by different organizational structures to capture the degree of reporting uncertainty and argue that reporting uncertainty is associated with two types of biases in the processing of information.

The documented empirical evidence suggests that loan officers are more uncertain about the quality of reporting received from franchisees than from outlets and bear greater decision biases toward them by overweighting franchise loan rate information when approving loans. At the other end of the interaction, franchise salespeople anticipate loan officers' decision biases and slant their loan rates downward (i.e., underreport risk) to reduce the foreseen likelihood of loan rejections. However, the higher default rate for franchisees suggests that the two types of biases (i.e., decision and reporting bias) do not perfectly offset each other. In sum, this study documents the cost of reporting uncertainty that arises from DMs' insufficient general knowledge about IPs.

Prior literature on issues related to information transmission has focused on either information use or information supply (reporting). This study investigates the implications of both simultaneously and sheds some light on their interaction. In addition, it highlights the role of reporting uncertainty and documents its cost (i.e., a higher default rate), which is all associated with organizational design. In particular, the finding that franchisees are associated with higher default rates demonstrates the real effect of reporting uncertainty. Although I document the costs associated with franchisees, there might also be benefits to franchising (e.g., increased business revenues) which have not been examined in this study. This study does not suggest that CAR made a suboptimal decision in franchising its loan business.

This study uses field data from one particular car dealership in Taiwan. I exploit several features of this research site, such as the fact that it possesses two business channels with different organizational structures and the organizational separation between information supply and decision rights, so as to document evidence on decision biases and reporting biases. The evidence is limited to one particular organization, but the underlying issue associated with the effects of reporting uncertainty on decision making and reporting has broader implications. Recognizing that internal information flow, decision rules, and organizational designs vary across firms, the empirical evidence specific to a given firm substantiates the general understanding of the interrelation between information use and reporting by offering concrete implications for a specific context.

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Appendix 1: Variable Descriptions

This table provides descriptions of the primary variables used in this study.

Variables	Description
BorrWithdrawal	=Dummy variable: 1 if the loan application is withdrawn by the borrower; 0 otherwise
LoanAccept	=Dummy variable: 1 if the loan application is approved by the loan officer; 0 otherwise
Default	=Dummy variable: 1 if a loan default occurs; 0 otherwise. For loans with complete payment histories, *Default* represents the occurrence of bad debt expenses; for loans without complete payment histories, it refers to cases where payment is overdue.
fChannel	=Dummy variable: 1 if the application was submitted through a franchisee; 0 if it was received from a company outlet
Rate	=The loan rate: the proxy for the borrower's credit risk, which is set by salespeople
Amount	=The approved loan amount
Term	=The loan payment term, ranging from 1 to 5 years
BorrGender	=Dummy variable: 1 if the borrower is male; 0 otherwise
EmpGender	=Dummy variable: 1 if the salesperson is male; 0 otherwise
EmpTenure	=The number of years employed at CAR
logEmpTenure	=Log of *EmpTenure*
Senior	=Dummy variable: 1 if *EmpTenure*>6; 0 if *EmpTenure*≤ 6

Appendix 2: Geographic Distribution of Loan Applications

This map shows the relative geographic position of each county in Taiwan and identifies the location of CAR's headquarters. The table below presents descriptive statistics on the number of company outlets in each county and the number of loan applications received, by county and channel. The statistics are based on the full sample, all of the loan applications.

County	Number of Company Outlets	Number of Loan Applications				
		Franchisees		Company Outlets		Total
Taipei	20	11738	53%	10520	47%	22258
Taoyuan	5	4220	71%	1739	29%	5959
Hsinchu	3	1956	62%	1177	38%	3133
Miaoli	2	978	49%	1027	51%	2005
Taichung	8	8882	63%	5129	37%	14011
Nantou	2	1505	67%	748	33%	2253
Changhua	3	2585	68%	1201	32%	3786
Yunlin	3	1796	62%	1086	38%	2882
Chiayi	2	2484	66%	1304	34%	3788
Tainan	5	5528	72%	2142	28%	7670
Kaohsiung	8	6442	70%	2707	30%	9149
Pingtung	2	2647	72%	1036	28%	3683
Yilan	1	1352	68%	650	32%	2002
Hualien	1	1256	69%	559	31%	1815
Taitung	1	1236	75%	410	25%	1646
Total	66	54605	63%	31435	37%	86040

Figure 1 CAR's Organizational Structure

Figure 1 presents CAR's organizational structure for its used-car loan business. At the bottom of the structure are two business channels: company outlets and franchisees. Franchisees are designated with a dashed line since they are independent organizations separate from CAR. Regional offices are positioned between the company headquarters and the two business channels in the hierarchy. The term "loan officers" as used in this paper refers to the employees responsible for dealing with loan approvals at either the regional offices or headquarters; "salespeople" refers to the employees working in either one of the two business channels.

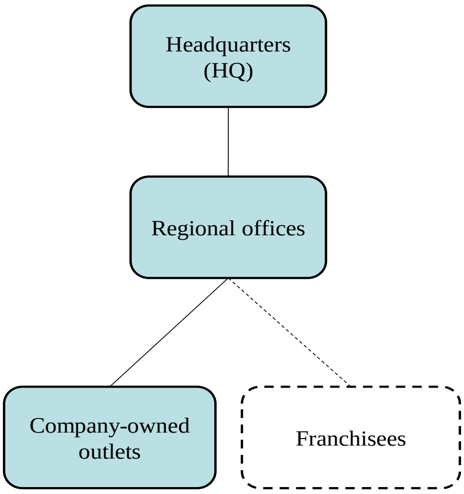

Figure 2 Sample Construction

Figure 2 illustrates the mapping for the loan application process and the sample construction. The full sample includes all applications received from borrowers, those both withdrawn and not withdrawn. The application sample includes only those applications that were not withdrawn, which were then either approved or rejected by loan officers. The approval sample includes the approved loans, which may or may not ultimately be in default.

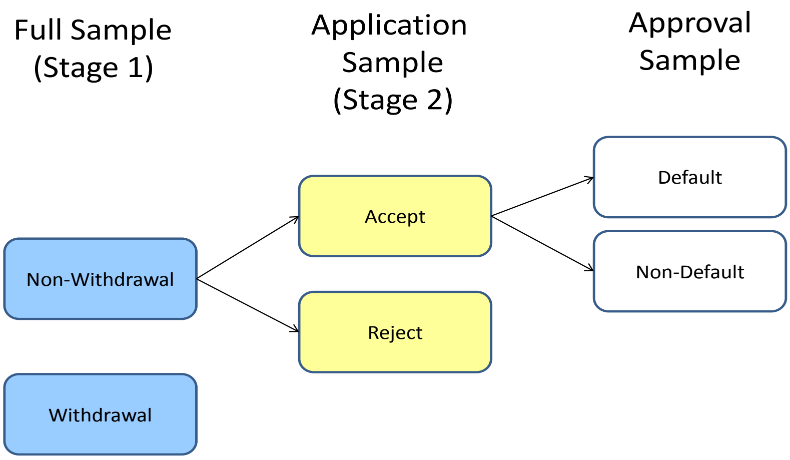

Table 1 Summary Statistics for the Full Sample

This table presents the descriptive statistics for loan applications in the full sample. Each variable is defined in Appendix 1. The full sample includes all loan applications, some of which were subsequently withdrawn by borrowers. Panel A outlines the summary statistics for loans from both franchisees and company outlets. Separate statistics for franchisees and outlets are reported in Panels B and C, respectively. Panel D reports the differences between franchisees and outlets. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Full Sample with Both Channels Included (N=86,040)

Variable	Mean	P25	Median	P75	Std. Dev.
BorrWithdrawal	0.157	0.000	0.000	0.000	0.364
fChannel	0.635	0.000	1.000	1.000	0.482
Rate	0.134	0.111	0.131	0.171	0.034
Amount (in 100,000)	2.847	1.500	2.500	3.500	1.918
Term	2.635	2.000	3.000	3.000	1.051
BorrGender	0.665	0.000	1.000	1.000	0.472

Panel B: Statistics for Franchisees in the Full Sample (N=54,605)

Variable	Mean	P25	Median	P75	Std. Dev.
BorrWithdrawal	0.155	0.000	0.000	0.000	0.362
Rate	0.133	0.111	0.131	0.161	0.032
Amount (in 100,000)	2.851	1.500	2.500	3.600	1.854
Term	2.701	2.000	3.000	3.000	1.071
BorrGender	0.668	0.000	1.000	1.000	0.471

Panel C: Statistics for Company Outlets in the Full Sample (N=31,435)

Variable	Mean	P25	Median	P75	Std. Dev.
BorrWithdrawal	0.161	0.000	0.000	0.000	0.368
Rate	0.137	0.111	0.132	0.178	0.035
Amount (in 100,000)	2.841	1.500	2.400	3.500	2.025
Term	2.519	2.000	2.500	3.000	1.007
BorrGender	0.660	0.000	1.000	1.000	0.474

Panel D: Differences between the Two Channels

Variable	Franchisees		Company Outlets		t-test	
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Mean	
BorrWithdrawal	0.155	0.362	0.161	0.368	-0.004	**
Rate	0.133	0.032	0.137	0.035	-0.005	***
Amount (in 100,000)	2.851	1.854	2.841	2.025	0.010	
Term	2.701	1.071	2.519	1.007	0.183	***
BorrGender	0.668	0.471	0.660	0.474	0.008	**

Table 2 Summary Statistics for the Application Sample

This table presents the descriptive statistics for loan applications in the application sample. The application sample includes only those loan applications that were not withdrawn by borrowers. Panel A outlines the summary statistics for loans from both channels. Separate statistics for the franchisees and company outlets are reported in Panels B and C, respectively. Panel D reports the differences between franchisees and outlets. Descriptions of the variables can be found in Appendix 1. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Application Sample with Both Channels Included (N=72,515)

Variable	Mean	P25	Median	P75	Std. Dev.
LoanAccept	0.860	1.000	1.000	1.000	0.347
fChannel	0.636	0.000	1.000	1.000	0.481
Rate	0.133	0.111	0.131	0.162	0.034
Amount (in 100,000)	2.790	1.500	2.400	3.500	1.835
Term	2.603	2.000	3.000	3.000	1.042
BorrGender	0.652	0.000	1.000	1.000	0.477

Panel B: Statistics for Franchisees in the Application Sample (N=46,149)

Variable	Mean	P25	Median	P75	Std. Dev.
LoanAccept	0.863	1.000	1.000	1.000	0.344
Rate	0.131	0.111	0.131	0.161	0.032
Amount (in 100,000)	2.803	1.500	2.500	3.500	1.789
Term	2.673	2.000	3.000	3.000	1.066
BorrGender	0.656	0.000	1.000	1.000	0.475

Panel C: Statistics for Company Outlets in the Application Sample (N=26,366)

Variable	Mean	P25	Median	P75	Std. Dev.
LoanAccept	0.853	1.000	1.000	1.000	0.354
Rate	0.136	0.111	0.132	0.178	0.035
Amount (in 100,000)	2.766	1.500	2.300	3.500	1.913
Term	2.479	2.000	2.000	3.000	0.988
BorrGender	0.644	0.000	1.000	1.000	0.479

Panel D: Differences between the Two Channels

Variable	Franchisees		Company Outlets		t-test	
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Mean	
LoanAccept	0.863	0.344	0.853	0.354	0.010	***
Rate	0.131	0.032	0.136	0.035	-0.005	***
Amount (in100,000)	2.803	1.789	2.766	1.913	0.037	***
Term	2.673	1.066	2.479	0.988	0.194	***
BorrGender	0.656	0.475	0.644	0.479	0.011	***

Table 3 Summary Statistics for the Approval Sample

This table presents the descriptive statistics for approved loan applications. Some loans have complete payment histories and some do not. The loans with complete payment histories are separated out as a sub-sample of the approval sample. Panel A separately outlines summary statistics for all loans that were approved (i.e., the entire approval sample) and only those with complete payment histories. Panels B and C report the differences in statistics between franchisees and company outlets within the approval sample and the sub-sample with complete payment histories, respectively. Descriptions of the variables can be found in Appendix 1. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Approval Sample

Variable	Approval Sample (N=62,332)		Complete Histories (N=19,159)	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Default	0.020	0.141	0.012	0.110
fChannel	0.639	0.480	0.595	0.491
Rate	0.131	0.033	0.131	0.034
Amount (in 100,000)	2.794	1.793	2.178	1.846
Term	2.584	1.043	1.521	0.479
BorrGender	0.638	0.481	0.648	0.478

Panel B: Differences between the Two Channels (Approval Sample)

Variable	Franchisees (N=39,837)		Company Outlets (N=22,495)		t-test	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Diff. in Mean**	
Default	0.023	0.150	0.016	0.124	0.007	***
Rate	0.129	0.032	0.134	0.035	-0.005	***
Amount (in100,000)	2.815	1.770	2.757	1.833	0.059	***
Term	2.658	1.068	2.453	0.985	0.205	***
BorrGender	0.642	0.480	0.630	0.483	0.012	***

Panel C: Differences between the Two Channels (Complete Histories)

Variable	Franchisees (N=11,404)		Company Outlets (N=7,755)		t-test	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Diff. in Mean**	
Default	0.010	0.097	0.014	0.118	-0.005	***
Rate	0.135	0.035	0.129	0.033	0.006	***
Amount (in100,000)	2.168	1.777	2.185	1.892	-0.018	
Term	1.530	0.480	1.515	0.479	0.015	**
BorrGender	0.654	0.476	0.643	0.479	0.012	*

Table 4 Pearson Correlation Table (Full Sample)

Table 4 reports Pearson correlation coefficients among variables using the full sample. Some correlations are null because some loans stop in the application process. For example, "borrower-withdrawn loans" cannot be approved by loan officers, so the correlation between *LoanAccept* and *BorrWithdrawal* is not valid. P-values are in parentheses. Please refer to Appendix 1 of this study for descriptions of each variable.

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)
(a)Rate	1.00									
(b)Amount	-0.33 (0.00)	1.00								
(c)Term	-0.04 (0.00)	0.403 (0.00)	1.00							
(d)BorrGender	0.09 (0.00)	-0.04 (0.00)	-0.01 (0.06)	1.00						
(e)EmpGender	-0.03 (0.00)	-0.01 (0.12)	-0.02 (0.00)	0.01 (0.11)	1.00					
(f)EmpTenure	-0.02 (0.00)	-0.01 (0.00)	-0.03 (0.00)	0.00 (0.18)	0.14 (0.00)	1.00				
(g)fChannel	-0.07 (0.00)	0.00 (0.46)	0.08 (0.00)	0.01 (0.01)	-0.02 (0.00)	-0.02 (0.00)	1.00			
(h)BorrWithdrawal	0.08 (0.00)	0.07 (0.00)	0.07 (0.00)	0.06 (0.00)	-0.03 (0.00)	-0.03 (0.00)	-0.01 (0.01)	1.00		
(i)LoanAccept	-0.17 (0.00)	0.01 (0.08)	-0.04 (0.00)	-0.07 (0.00)	0.00 (0.51)	0.02 (0.00)	0.01 (0.00)	. .	1.00	
(j)Default	0.09 (0.00)	-0.01 (0.00)	0.06 (0.00)	0.04 (0.00)	0.00 (0.79)	-0.01 (0.00)	0.02 (0.00)	. .	. .	1.00

Table 5 Loan Approval Decisions (Application Sample)

$$LoanAccept_i=\alpha_1 Rate_i+\alpha_2 fChannel_j+\alpha_3 Rate_i*fChannel_j+\Sigma\alpha_i Control_i+LocationFE_k+YearFE_t+\varepsilon_{i,} \quad (1)$$

Table 5 presents the results for the regression of the loan approval decisions based on loan rates. This model is estimated by a linear probability model at the loan application level using the application sample. Columns (1), (2), and (3) report results based on the application sample pooled with each of the two business channels. Columns (4) and (5) report regression results for franchisees and company outlets, respectively. A Wald test is performed to test the difference in the coefficients for *Rate* between the two channels and the chi-squared value is reported. Standard errors are clustered at the salesperson level and reported in parentheses. Please refer to Appendix 1 and Figure 2 of this study for descriptions of each variable and a definition of the sample construction, respectively. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	Application Sample			Franchisees	Company Outlets
	(1)	(2)	(3)	(4)	(5)
Rate	-1.875***	-1.873***	-1.613***	-2.034***	-1.617***
	(0.058)	(0.058)	(0.071)	(0.072)	(0.078)
fChannel		0.002	0.061***		
		(0.003)	(0.010)		
Rate*fChannel			-0.441***		
			(0.083)		
Amount	-0.792***	-0.790***	-0.790***	-0.706***	-0.892***
	(0.097)	(0.097)	(0.096)	(0.111)	(0.159)
Term	-0.126***	-0.126***	-0.126***	-0.096***	-0.193***
	(0.013)	(0.013)	(0.013)	(0.016)	(0.025)
BorrGender	-0.042***	-0.042***	-0.043***	-0.042***	-0.045***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Constant	1.192***	1.190***	1.155***	1.198***	1.185***
	(0.017)	(0.017)	(0.018)	(0.018)	(0.026)
Test of the difference: *Rate*				-0.417***	
χ^2 statistics				20.00	
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Location fixed effect	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.043	0.043	0.043	0.048	0.038
Observations	72,515	72,515	72,515	46,149	26,366

Table 6 Loan Rate Setting Decisions (Full Sample)

$$Rate_i = \beta_1 \, fChannel_j + \Sigma\beta_i Control_i + LocationFE_k + YearFE_t + v_i, \tag{2}$$

Table 6 presents results for the regression of loan rates based on business channels. This model is estimated by OLS regressions at the loan application level using the full sample. Column (1) reports the results based on the full sample. Columns (2) and (3) show the results for each sub-sample, split according to whether the borrowers withdrew their applications or not. Columns (4) and (5) report regression results for loans approved by loan officers and for loans rejected by either borrowers or loan officers, respectively. A Wald test is performed to test the difference in the coefficients for *fChannel* between the two sub-samples, and the chi-squared values are reported. Standard errors are clustered at the salesperson level and reported in parentheses. Please refer to Appendix 1 and Figure 2 of this study for descriptions of each variable and the definition of the sample construction, respectively. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	Full Sample	Executed (BorrWithdrawal=0)	Non-Executed (BorrWithdrawal=1)	Executed (LoanAccept=1)	Non-Executed (LoanAccept=0)
	(1)	(2)	(3)	(4)	(5)
fChannel	-0.504***	-0.540***	-0.274***	-0.546***	-0.309***
	(0.049)	(0.047)	(0.088)	(0.047)	(0.066)
Amount	-0.654***	-0.699***	-0.532***	-0.743***	-0.507***
	(0.016)	(0.016)	(0.025)	(0.015)	(0.023)
Term	0.337***	0.327***	0.336***	0.318***	0.265***
	(0.020)	(0.020)	(0.038)	(0.020)	(0.033)
BorrGender	0.522***	0.506***	0.299***	0.471***	0.208***
	(0.022)	(0.025)	(0.061)	(0.027)	(0.045)
Constant	14.49***	14.50***	15.30***	14.41***	15.66***
	(0.206)	(0.217)	(0.271)	(0.208)	(0.239)
Test of the difference:					
fChannel		-0.266***		-0.237***	
χ^2 statistics		11.32		18.16	
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Location fixed effect	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.189	0.193	0.196	0.206	0.169
Observations	86,040	72,515	13,525	62,332	23,708

Table 7 Loan Default

Panel A: Approval Sample with Both Complete and Incomplete Payment Histories

$$Default_i=\gamma_1 Rate_i+\gamma_2 fChannel_j+\gamma_3 Rate_i*fChannel_j+\Sigma\gamma_i Control_i+OutletFE_k+YearFE_t+\delta_{i,} \quad (3)$$

Table 7 shows results for the regression of loan default based on loan rates. This model is estimated by either OLS or logit regressions at the loan application level using the approval sample. Columns (1), (4), and (5) report results based on the application sample pooled with each of the two business channels. Columns 2 and 3 report regression results for franchisees and company outlets, respectively. A Wald test is performed to test the difference in the coefficients for *Rate* between the two channels, and the chi-squared value is reported. Standard errors are clustered at the salesperson level and reported in parentheses. Please refer to Appendix 1 and Figure 2 of this study for descriptions of each variable and the definition of the sample construction, respectively. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	Approval Sample (OLS) (1)	Franchisees (OLS) (2)	Company Outlets (OLS) (3)	Approval Sample (OLS) (4)	Approval Sample (Logit) (5)
Rate	0.266***	0.447***	0.258***	0.370***	20.38***
	(0.030)	(0.029)	(0.031)	(0.022)	(1.005)
fChannel	-0.016***			0.008***	0.439***
	(0.004)			(0.001)	(0.074)
Rate*fChannel	0.177***				
	(0.038)				
Amount	0.020	-0.029	0.106	0.019	-79.62***
	(0.335)	(0.465)	(0.491)	(0.334)	(30.57)
Term	0.795***	0.872***	0.604***	0.795***	49.28***
	(0.063)	(0.078)	(0.089)	(0.063)	(3.352)
BorrGender	0.010***	0.010***	0.010***	0.010***	0.583***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.068)
Constant	-0.049***	-0.066***	-0.044***	-0.062***	-8.897***
	(0.006)	(0.006)	(0.007)	(0.005)	(0.360)
Test of the difference: *Rate*		0.189***			
χ^2 statistics		21.01			
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Location fixed effect	Yes	Yes	Yes	Yes	Yes
Adjusted R^2 /Pseudo R^2	0.015	0.015	0.014	0.015	0.084
Observations	62,332	39,837	22,495	62,332	62,332

Table 7 Loan Default (continued)

Panel B: Approval Sample with Complete Payment Histories Only

$Default_i = \gamma_1 Rate_i + \gamma_2 fChannel_j + \gamma_3 Rate_i * fChannel_j + \Sigma\gamma_i Control_i + OutletFE_k + YearFE_t + \delta_{i,}$ (3)

Variables	Approval Sample (OLS) (1)	Franchisees (OLS) (2)	Company Outlets (OLS) (3)	Approval Sample (OLS) (4)	Approval Sample (Logit) (5)
Rate	0.147***	0.261***	0.144***	0.209***	0.145***
	(0.035)	(0.037)	(0.036)	(0.027)	(0.036)
fChannel	-0.010*				
	(0.005)				
Rate*fChannel	0.113**				
	(0.046)				
Amount	-0.162	-0.229	0.004	-0.202	0.006
	(0.273)	(0.331)	(0.459)	(0.274)	(0.460)
Term	0.769***	0.830***	0.641**	0.769***	0.641**
	(0.177)	(0.236)	(0.259)	(0.177)	(0.261)
BorrGender	0.006***	0.006**	0.007***	0.006***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	-0.032***	-0.044***	-0.027***	-0.040***	-0.026**
	(0.008)	(0.007)	(0.010)	(0.007)	(0.010)
Test of the difference: *Rate*		0.117**			
χ^2 statistics		5.56			
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Location fixed effect	Yes	Yes	Yes	Yes	Yes
Adjusted R^2 /Pseudo R^2	0.008	0.007	0.010	0.008	0.102
Observations	19,159	11,404	7,755	19,159	18,181

Table 8 Re-estimation with Non-linear Probability Models

Panel A: Loan Withdrawal and Approval Decisions

Panel A reports the results of Models 1 and 3, re-estimated at the loan application level by logit regressions. Standard errors are clustered at the salesperson level and reported in parentheses. Columns 1 and 2 present the results for loan approval decisions and loan defaults, respectively. Panel B reports the average marginal effects of loan rates on loan approval decisions and loan defaults by channel based on the results of Panel A. Please refer to Appendix 1 and Figure 2 of this study for descriptions of each variable and the definition of the sample construction, respectively. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	**LoanAccept** (1)	**Default** (2)
Rate	-13.77***	19.73***
	(0.593)	(1.918)
fChannel	0.624***	0.301
	(0.106)	(0.330)
Rate*fChannel	-4.247***	0.893
	(0.709)	(2.135)
Amount	-5.817***	-79.78***
	(0.789)	(30.61)
Term	-1.201***	49.32***
	(0.120)	(3.359)
BorrGender	-0.404***	0.583***
	(0.0251)	(0.0677)
Constant	4.476***	-8.797***
	(0.160)	(0.444)
Year fixed effect	Yes	Yes
Outlet fixed effect	Yes	Yes
Pr > χ^2	0.000	0.000
Pseudo R^2	5.66%	8.43%
Log-likelihood	-27785.346	-5682.7136
Observations	72,515	62,332

Panel B: Average Marginal Effect of the Loan Rate

	Pr(LoanAccept)	*Pr(Default)*
Franchisees	-2.019***	0.454***
	(0.064)	(0.029)
Company outlets	-1.648***	0.300***
	(0.074)	(0.036)
Interaction effects	-0.371***	0.154***
	(0.094)	(0.058)

Table 9 Effect of Salespeople's Tenure

These results are estimated at the loan application level by OLS regression. All analyses are limited to the loan applications received from company outlets. Columns (1) and (2) use the outlet applications from the approval sample. The median of salespeople's tenure is six years, according to which I split the sample into senior and junior salespeople. A Wald test is performed to test the difference in the coefficients for *Rate* between the sub-samples, and the chi-squared value is reported. The sample used for Column (3) includes outlet approved loans. Standard errors are clustered at the salesperson level and reported in parentheses. Please refer to Appendix 1 and Figure 2 of this study for descriptions of each variable and the definition of the sample construction, respectively. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	LoanAccept		*Default*
	(1)	(2)	(3)
Variables	(Senior=1)	(Senior=0)	
Rate	-1.393***	-1.958***	0.258***
	(0.093)	(0.131)	(0.031)
Senior			-0.0002
			(0.002)
Amount	-0.606***	-1.417***	0.107
	(0.183)	(0.275)	(0.494)
Term	-0.216***	-0.141***	0.604***
	(0.029)	(0.043)	(0.088)
BorrGender	-0.040***	-0.052***	0.010***
	(0.005)	(0.008)	(0.002)
Constant	1.157***	1.228***	-0.044***
	(0.035)	(0.041)	(0.006)
Test of the difference: *Rate*	0.565***		
χ^2 statistics	12.47		
Year fixed effect	Yes	Yes	Yes
Location fixed effect	Yes	Yes	Yes
Observations	16,430	9,936	22,495
Adjusted R^2	0.034	0.047	0.014