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Specialists and Generalists in Adaptive Organizations

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Abstract

This study examines the optimal organizational composition of specialists and generalists theoretically and empirically, using a model based on Dessein and Santos (2006). It assumes that specialists excel in adaptation given their deep knowledge in specific areas but face coordination challenges given limited knowledge of other areas. In contrast, generalists benefit from broad task experience, making them superior in coordination but less effective in adaptation than specialists. The model predicts the following monotonicity: the optimal organizational structure shifts from one with many specialists to one with many generalists as the importance of coordination (relative to adaptation) increases or as market uncertainty increases under the condition that the importance of coordination is sufficiently high. These predictions are tested using employee assignment history data from a large Japanese trading company. The dataset includes employees who joined the company in fiscal year 1984 or later and their records up to fiscal year 2023. As predicted, divisions in commodity trading, where adaptation to their market condition is relatively crucial, have more specialists than divisions in business investment, where coordination is key. Among the business investment divisions, the proportion of generalists is higher in those with higher market uncertainty.

Keywords: Human capital development, Career, Specialists and generalists, Training, Job assignment.

JEL classification: J24, M50, M53, M54

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1 Introduction

Human capital development policies for employees within firms are crucial for organizational growth. These policies are closely linked to job assignment policies, which involve determining the allocation of employees with specific competencies to various departments. There are two main approaches: (1) developing multi-skilled workers through job rotation (generalists) and (2) assigning workers to specific roles to enhance their expertise (specialists)[1]. The merits of specialists versus generalists remain debated; nonetheless, effective human capital development policies through job assignment should be tailored to the skills of employees and organizational circumstances.

Two key elements are essential within organizational economic theory to address the issue of human capital development strategies. The first is *adaptation*, which requires employees to align actions with changing market conditions, such as shifts in market demands and technological advancements. The second element is *coordination*, which involves employees performing complementary actions in cooperation with one another. As organizational work is often collaborative, individual efforts alone are insufficient for effective management. Effective coordination, including communication, feedback, and leadership among team members and across teams, is crucial for improving organizational performance.

Traditionally, Aoki (1986) categorizes coordination in organizations into two types: (1) *vertical coordination*, where workers are specialized based on a centralized job classification system, as commonly seen in the U.S., and (2) *horizontal coordination*, where workers are multi-skilled, and coordination is achieved through delegation, as observed in Japan. Decision-making in the U.S. tends to follow a top-down approach, while in Japan, it is traditionally bottom-up. Morita (2005) explains the difference in practices between the U.S. and Japan through the multiple equilibria, focusing on multiskilling, delegation, and continuous process improvement[2]. In the Japanese equilibrium, all firms conduct the improvement through employees, by providing them with multiple skills, which leads to a horizontal organizational structure. However, in the U.S. equilibrium, firms do not conduct the improvement, nor do they provide their employees with multiple skills, which promotes a vertical structure.

Dessein and Santos (2006), a key reference for this paper, build on the concepts of coordination and adaptation in the context of team production. The research examines the relationship between specialization and coordination in organizations adapting to a changing environment. Alonso, Dessein, and Matouschek (2015) expands on adaptive organization theory by introducing competition (price sensitivity of demand), demonstrating that a centralized structure may be more effective in adaptation than decentralization even when division managers possess superior information about local conditions and incentive conflicts are minimal.

In this paper, I derive the optimal organizational composition based on two types of workers: specialists and generalists, using the model from Dessein and Santos (2006). Specialization is defined by the intensity of task experiences given the same tenure: specialists focus on a single task as skilled workers, while generalists are multi-skilled through multi-task experience. Each type has distinct characteristics. Specialists possess deep expertise in their specific area, making them highly adaptable, but they face challenges with coordination owing to their limited knowledge outside their area of specialization. Generalists, with broad experience, excel in coordination but are less adaptable owing to their limited specialization.

I theoretically and empirically address three key questions: (1) What is the optimal composition of specialists and generalists in an organization? (2) How does the optimal composition vary with organizational and market parameters? (3) How do model predictions align with actual firms? The model incorporates parameters tied to organizational profitability. First, it considers the importance of adaptation and coordination, which influence costs for organizations arising from failures in either dimension. Second, market uncertainty impacts organizational costs. The model uses the probabilities of adaptation and coordination success for specialists and generalists as indicators of their skills. Spe-

[1] Ortega (2001) theoretically compares job rotation and specialization assignment policies, showing that job rotation is beneficial when uncertainty in employee productivity and technology is high.

[2] Continuous process improvement involves a number of small changes to enhance product quality or reduce production costs, which are basically unobservable outside the firm (Morita, 2001, 2005).

cialists are assumed to have a higher probability of adaptation success, while generalists are assumed to perform coordination flawlessly. Specialists, however, only succeed in coordination with limited probability. Lastly, the model accounts for training costs: educating workers to become generalists through job rotation incurs productivity losses and is costlier for organizations, while training specialists is cheaper owing to their accumulation of human capital with minimal productivity loss.

Based on this model, I offer the following empirical predictions: (1) Organizations with higher coordination (relative to adaptation) demands will have more generalists; (2) When coordination is sufficiently important, organizations in high uncertainty environments will have a greater proportion of generalists compared to those in stable environments. These predictions reflect the monotonic shift in organizational composition, from specialist-dominated to generalist-dominated, depending on changes in the organizational and market parameters.

I examine whether these predictions hold in real firms by analyzing a large Japanese trading company with operations both domestically and internationally. This company's business field can be grouped into seven main areas: Consumer Business, Infrastructure, Energy, Agriculture, Machinery, Chemicals, and Metals. Japanese trading companies generally engage in two business types: (1) commodity trading, which connects the demanders and suppliers of products, and (2) business investment, where the firm invests in other companies to enhance their value and create synergies by providing management resources, including human resources, funds, information, and expertise. For this analysis, Machinery, Chemicals, and Metals are categorized as commodity trading areas, as they primarily handle products within their respective fields and trade them with customers. Meanwhile, Consumer Business, Infrastructure, Energy, and Agriculture are classified as business investment areas, as they manage project-based investment.

To understand the differences between business investment and commodity trading, I conducted interviews with managers in Consumer Business and with those in Chemicals. I found that the primary distinction lies in their management priorities: managers in Consumer Business emphasize frequent meetings with directors and other managers to share and communicate information within the business area, while the managers in Chemicals focus on product knowledge and advanced technologies. This suggests that coordination is more important in business investment, whereas adaptation is crucial in commodity trading.

I test two empirical hypotheses. First, commodity trading divisions, where adaptation is more crucial, have a higher proportion of specialists than business investment divisions. Second, among business investment divisions, where coordination is essential, the proportion of generalists is higher in those with higher market uncertainty.

Specialization is measured using workers' assignment history records from the fiscal year 1984 to 2023, which includes text data on the divisions and departments to which employees were assigned. First, four simple measures were created: (1) the total number of business areas each worker experienced during their career, (2) a specialist dummy variable, indicating whether a worker experienced only one business area, (3) a broader specialist dummy variable for worker's experience of up to two business areas, and (4) the proportion of a worker's experience in their current business area as of 2023.

Additionally, I developed a career intensity variable, calculated using Latent Dirichlet Allocation (LDA), an unsupervised machine-learning algorithm developed by Blei, Ng, and Jordan (2003). LDA identifies latent topics in text data, and has recently been used in economics to measure CEO behavior (Bandiera, Prat, Hansen, and Sadun, 2020; Englmaier, Hofmann, and Wolter, 2023). By analyzing word occurrences in assignment records, LDA estimates the weights of career topics for each worker, with those concentrating on one topic considered specialists. The Herfindahl-Hirschman Index (HHI) quantifies this concentration, with higher values indicating greater specialization. Career intensity, which incorporates detailed text information from assignment records, is more accurate than the other indices for capturing specialization, as it accounts for rotations within and across business areas.

Market uncertainty is measured using Market Beta, which indicates how sensitive a stock or investment portfolio is to market movements. I calculated the mean Market Beta for the industries in each of the seven business areas of J-Trading using the average Market Beta for the past 60 months (up to May 2024) for 33 industries listed on the Tokyo Stock Exchange[3].

Ordinary Least Squares was used to estimate each specialization index at the worker level, controlling for worker attributes. The results show that commodity trading divisions have a higher degree of specialization than business investment divisions, consistent with the model's predictions. Additionally, the estimations indicate that the proportion of generalists in the business investment divisions is positively correlated with market uncertainty.

The contribution of this study is that it is the first to analyze the optimal composition of specialists and generalists in the context of coordination and adaptation. The optimal authority of organizational structure has been a subject of ongoing debate, particularly regarding whether environmental shifts will lead to centralization or decentralization. Alonso, Dessein, and Matouschek (2008) argue that centralization dominates decentralization when both the relative importance of coordination and the own-division bias are high. Empirical evidence supporting this point is provided by Asuyama (2020), who uses the worker-level data on decentralization and social capital, alongside industry-level data on coordination needs across 14 countries. In another study, Dessein, Lo, and Minami (2022) empirically examine the relationship between local environmental volatility and organizational structure, particularly the degree of decentralization and centralization, using data from a large Japanese retailer. Kato and Owan (2011) develop a theoretical framework based on Dessein and Santos (2006), suggesting that as the importance of adaptation increases, firms are more likely to adopt a horizontal coordination system and invest in horizontal communication channels. They demonstrate the consistency of their framework with data from a survey of Japanese firms.

Previous theoretical studies, including Dessein and Santos (2006), typically assume a homogeneous workforce, focusing on identical workers with optimal skill sets. However, worker skills exhibit heterogeneity, with some excelling in specialized knowledge and others in coordination skills from broad experience. Developing worker skills uniformly is often undesirable, and organizations should tailor recruitment and training to align with workforce composition and market conditions. Discussions on the characteristics of skills possessed by workers remain undeveloped. This study addresses that gap by analyzing the optimal organizational structure considering the heterogeneous workforce. It suggests that firms can enhance competitiveness by tailoring worker development to workforce characteristics.

While the literature on specialists and generalists typically focuses on individual choices and competencies, few studies explore the optimal composition of specialists and generalists from an organizational perspective, considering the trade-offs between adaptation and coordination. In individual choices, Anderson (2012) theoretically shows that the decision to become a specialist or a generalist within an organization depends on problem complexity and disciplinary boundaries.

The advantages of specialists versus generalists vary by context. Buchen, Kragl, and Palermo (2021) find that specialists outperform generalists under multitasking, even if specialists are slightly less competent. Specialists have a productivity advantage in the presence of greater product-market volatility (DeVaro and Farnham, 2011; DeVaro and Gürtler, 2016) as indicated by product price fluctuations. Conversely, generalists benefit from worker mobility. In occupation-level analysis, industry-specific specialists are less mobile across industries and are more vulnerable to wage shocks than generalists (Hervé, 2023). Generalists are less affected by involuntary job displacement (Byun and Raffiee, 2023), and their broader knowledge allows them to facilitate the acquisition of transferable skills by others (Fahrenkopf, Guo, and Argote, 2020). Generalists also tend to succeed in leadership roles, especially when decision-making requires broad knowledge. Previous studies suggest that generalists are more likely to attain executive leadership positions (Lazear, 2012; Frederiksen and Kato, 2018), and organizational profit increases with a leader's expertise breadth if the business operates in uncertain conditions (Ferreira and Sah, 2012). Additionally, Custódio, Ferreira, and Matos (2013) show that generalist CEOs earn more than specialist CEOs, highlighting the value of general human capital over firm-specific human capital.

While this literature focuses on individual characteristics and capabilities, it does not address the broader organizational context—specifically, how the assignment of specialists and generalists affects

[3]Data is sourced from https://costofcapital.jp/ with permission (in Japanese).

organizational performance. The key challenge for firms is to match workers with roles that align with their skills and the job's requirements. Prasad (2009) uses a principal-agent model and shows that optimal contracts stipulate that generalists are assigned to multitask, whereas specialists are assigned to the task they are specialized in. Zambrana and Zapatero (2021) demonstrate the importance of proper talent assignment using data from asset management firms, showing that it can enhance firm performance. However, these studies focus on individual job assignments rather than considering the policies for the entire firm, such as organizational compositions of labor force[4].

In examining organizational productivity, it is essential to consider how specialists and generalists are trained and assigned tasks based on organizational and worker characteristics. Few studies have explored this issue from the perspective of organizational structure. This study analyzes the organization as a whole rather than focusing solely on individual specialists or generalists, by constructing a model that addresses intra-organizational coordination. This approach provides valuable insights for firms making competitive decisions about human capital development policies.

The remainder of the paper is structured as follows. Section 2 develops the model of organizational composition of specialists and generalists based on Dessein and Santos (2006). Sections 3 and 4 introduce the firm data and measurement of specialization, respectively. Section 5 outlines the empirical strategy to assess the consistency of the model's predictions with the firm data, and Section 6 presents the results. Section 7 concludes the paper.

2 Model

This section presents a theoretical model of optimal organizational composition aimed at maximizing organizational profit. The model builds upon Dessein and Santos (2006), in which workers take action to adapt their local information and coordinate their tasks with other workers. Unlike Dessein and Santos (2006), which assumes identical workers, I distinguish between two types of workers—specialists and generalists—and identify the conditions under which each organizational composition is optimal.

2.1 The Setting

2.1.1 Worker types and the organizational composition

Consider an organization with two workers, $i \in \{1, 2\}$, each responsible for a separate task: worker 1 handles task 1, and worker 2 handles task 2. The workers are categorized into two types: specialists and generalists. The type of worker i is denoted as $t_i \in \{s, g\}$, where s represents a specialist and g a generalist. A specialist possesses deep expertise in a specific area, while a generalist has broad, multi-disciplinary skills. The organization can therefore adopt one of three compositions: (1) Specialist-Specialist (S-S), (2) Generalist-Generalist (G-G), or (3) Specialist-Generalist (S-G).

Organizations where specialists and generalists coexist suggest the presence of complementarities between the two. Typically, a generalist is assumed to hold a managerial position with decision-making authority above specialists, who act as team members[5]. However, this model assumes that specialists and generalists operate on equal footing within the organization. The model shows that, under a certain condition, when the counterpart is a generalist, assigning a specialist to another task is more optimal than assigning a generalist. This implies that a balanced assignment of specialists and generalists can be optimal even in horizontal relationships. The complementarity between generalists and specialists is particularly pronounced when the importance of coordination differs across organizations[6].

[4] Prasad (2009) incorporates q denoted as the fraction of specialists and generalists, but do not discuss the optimal q in the model.

[5] For example, Ferreira and Sah (2012) discuss a hierarchical model in which specialists gather information under generalists who hold decision-making authority within an organization. In a similar vein, Lazear (2012) and Frederiksen and Kato (2018) argue that leaders in organizations tend to be generalists.

[6] For example, the Agriculture area at J-Trading, which is part of the dataset used in my empirical analysis, includes both a fertilizer trading business and an agricultural platform business within the same department. Assigning specialists to the fertilizer trading side, which requires deep expertise in agricultural markets, and generalists to the platform side,

Before production begins, the organization hires two identical workers and trains them according to the chosen composition. The training costs, h_{t_i}, depend on the worker types. For example, a specialist accumulates specific human capital by focusing exclusively on task i, whereas a generalist gains multi-functional human capital through job rotation. The training period is assumed to be identical for specialists and generalists, meaning that the tenures of workers 1 and 2 are equal.

Assumption (Training costs)**.** $h_s < h_g$.

This assumption means that training a generalist is more costly than training a specialist. Training specialists is relatively inexpensive, as they continue to accumulate human capital in their specific areas with minimal productivity loss (DeVaro and Gürtler, 2016). In contrast, training generalists involves exposure to multiple areas, which incurs some productivity loss for the organization, as they must learn new domain knowledge and skills in each transfer. Consequently, developing a generalist's human capital is more costly for the organization than that of a specialist. This assumption is based on the idea that specialists accumulate human capital through on-the-job training within the organization, as their expertise aligns with the organization's specific needs, whereas generalists accumulate human capital through broader experience by job rotation, which supports horizontal coordination needs. It is possible that $h_s > h_g$ if one assumes that firms develop specialists' general adaptation skills primarily through off-the-job training, as is often the case in IT companies. In this case, companies incur additional training costs other than on-the-job training costs. However, large Japanese companies—including the trading company used in my empirical analysis—typically rely on on-the-job training and job rotation. In this context, the trading company requires specialists to adapt to specific business areas, while generalists are expected to coordinate across workers and departments. Consistent with the empirical analysis using data from large Japanese firms, it is natural that the assumption that $h_s < h_g$ holds[7].

This assumption is supported by previous literature, such as Campion and McClelland (1991, 1993), which highlight the additional training costs associated with job rotation, as workers must be taught new roles. Morita (2005) incorporates the cost for a firm to provide multiskills to workers, which is higher than for a single task, in his model. Dessein and Santos (2006) also emphasize that it takes considerable time for generalists to develop a broad skill set.

A key distinction between specialists and generalists is their strengths and weaknesses. Specialists excel in their areas of expertise but lack knowledge in other areas owing to their narrow focus. In contrast, generalists possess a wide range of knowledge from diverse experiences but less depth in any particular area. In this model, specialists are superior to generalists in terms of adaptation, while generalists excel in coordination. Additionally, I assume that each specialist in the organization specializes in a different area. Even with two specialists, their ability to coordinate is limited owing to the lack of cross-area knowledge, also assumed in the model of Ferreira and Sah (2012).

2.1.2 Adaptation and coordination

An organization's profit depends on two factors: (1) the adaptation of each task to the organizational environment and (2) the coordination between tasks. In the adaptation stage, worker i takes a primary action a_{ii} based on local information θ_i, which represents private market information to achieve task i, only observed by worker i. The local information θ_i follows a common distribution, $\theta_i \sim N(0, \sigma_\theta^2)$, where σ_θ^2 represents the variance that reflects the uncertainty of the worker's business environment and is common across all workers. Local information θ_i includes both market demand and supply conditions relevant to each task. Therefore, the primary action a_{ii} broadly represents decision-making behavior in corporate activities[8]. Adaptation measures how closely worker i's primary action a_{ii} aligns with θ_i. Perfect adaptation occurs when $a_{ii} = \theta_i$. In addition to adaptation, workers must coordinate

which demands broad knowledge such as digital transformation and solutions for environment-friendliness, may produce complementary effects through differentiated task allocation.

[7] This assumption is critical to the model, as it affects the results in Proposition 2. Specifically, the direction of monotonicity reverses as uncertainty increases if $h_s > h_g$, as detailed in footnote 14.

[8] Consider, for example, the chemical department of a trading company, which consists of a procurement team and a sales team. The procurement team determines the order quantity of chemical products based on price information and

their tasks. Complementary actions are denoted by a_{ji}, where task i is coordinated with task $j \neq i$. Coordination refers to how closely worker j's complementary action a_{ji} aligns with worker i's primary action a_{ii}. Perfect coordination occurs when $a_{ji} = a_{ii}$. Coordination between the primary action a_{ii} and the complementary action a_{ji} illustrates the trade-off between adaptation and coordination, as tasks are interdependent[9].

2.1.3 Objective functions

This model incorporates adaptation and coordination losses as proxies for organizational profit. The cost function for worker i's losses, including training costs, is expressed as:

$$c_i = \phi(a_{ii} - \theta_i)^2 + \beta(a_{ji} - a_{ii})^2 + h_{t_i}, \quad i, j \in \{1, 2\},\ j \neq i,$$

where the deviation between the primary action a_{ii} and local information θ_i represents adaptation losses, and the gap between complementary action a_{ji} and the primary action a_{ii} reflects the coordination losses. The parameters $\phi > 0$ and $\beta > 0$ denote the importance of adaptation and coordination, respectively, indicating how the failure of adaptation or coordination influences the costs.

Assumption (Team production)**.** *The organization selects an optimal composition from S-S, S-G, and G-G, and worker i then takes optimal actions a_{ii}^* and a_{ij}^* to minimize the total expected cost function $E[C] = E[c_1] + E[c_2]$.*

The second assumption implies that both the organization and the workers will make optimal choices to minimize their cost functions without any conflict of interest under the following assumptions.

Let $p_\theta^{t_i}$ denotes the probability that worker i, with type t_i, observes local information.

Assumption (Adaptation)**.** $p_\theta^s > p_\theta^g$

The third assumption represents that specialists have a strictly higher probability of observing local information than generalists owing to the specialist's advantage in adaptation. Specialists accumulate human capital in their field through learning by doing, enabling them to excel at observing local information. The probability $p_\theta^{t_i}$ is public information, dependent solely on t_i not θ_i. When worker i can observe θ_i, they choose an optimal primary action that minimizes their costs:

$$a_{ii}^* = \arg\min_{a_{ii}} \ \phi(a_{ii} - \theta_i)^2 + \beta(a_{ji} - a_{ii})^2.$$

If worker i cannot observe θ_i with probability $1 - p_\theta^{t_i}$, their primary action is the expected value of θ_i. Thus, $a_{ii}^* = E[a_{ii}] = E[\theta_i] = 0$.

Assumption (Coordination)**.** *$a_{ji} = a_{ii}$ if worker j's type $t_j = g$, while $a_{ji} = E[a_{ii}]$ if $t_j = s$.*

Generalists, with their broad range of knowledge base, are assumed to comprehend how the other worker adapts to their environment. Therefore, I assume that a generalist can observe their counterpart's primary action and coordinate perfectly, meaning $a_{ji} = a_{ii}$[10]. In contrast, specialists, with

sales forecast (a_{ii}), while the sales team decides which products to sell and in what quantity based on customer demand (a_{jj}).

[9] Continuing with the chemical department example, suppose the procurement team places a large order in response to falling prices of chemical products, while the sales team shifts its focus to different products owing to declining customer demands. This misalignment may result in poor inventory management, which can be costly for the organization. To address this, both teams must communicate and attempt to align their actions: for instance, the sales team may lower the price to help inventory management (a_{ji}), while the procurement team may explore new procurement sources (a_{ij}). When coordination is imperfect, both teams may deviate from their optimal actions in favor of coordination. This trade-off is reflected in the optimal primary action a_{ii}^*, as shown in Table 1.

[10] The assumption of perfect coordination is an extreme case. However, if I relax this assumption by introducing a probability $q_c^{t_i}$ of observing the counterpart's primary action, with $q_c^g > q_c^s$, the model's results do not change significantly (see Appendix A.5). Thus, I retain the simplified model where generalists can implement perfect coordination, and specialists cannot coordinate.

limited knowledge outside their expertise, cannot observe the counterpart's primary action. Consequently, a specialist's complementary action is the expected value of the counterpart's primary action, $a_{ji} = E[a_{ii}] = E[\theta_i] = 0$.

To summarize, the total expected costs for the organization are:

$$E[C|t_i, t_j] = \sum_{i=1}^{2} \left\{ p_\theta^{t_i} E[c_i^{Observed}|t_i, t_j] + (1 - p_\theta^{t_i}) E[c_i^{Not\ Observed}|t_i, t_j] \right\}, \tag{1}$$

where $c_i = \phi(a_{ii} - \theta_i)^2 + \beta(a_{ji} - a_{ii})^2 + h_{t_i}$, $i, j \in \{1, 2\}$ and $j \neq i$. Here, $c_i^{Observed}$ represents the cost when worker i can observe the local information θ_i with probability $p_\theta^{t_i}$, while $c_i^{Not\ Observed}$ refers to the case when θ_i is not observed with probability $1 - p_\theta^{t_i}$. In the former case, the optimal a_{ii} minimizes the cost function, while in the latter case, $a_{ii} = 0$. This formulation captures how product costs are influenced by worker actions, with key parameters including: (1) importance of adaptation ϕ, (2) importance of coordination β, (3) probability of observing local information $p_\theta^{t_i}$, (4) variance of information σ_θ^2, and (5) training cost h_{t_i}.

2.1.4 Timing

The timing of the production decision-making process is as follows:

1. The organization selects its organizational type—S-S, G-G, or S-G—based on the observed values of the following parameters: the importance of adaptation (ϕ), the importance of coordination (β), uncertainty (σ_θ^2), training costs (h_{t_i}), and the observation probabilities of local circumstances ($p_\theta^{t_i}$).

2. The organization hires and trains worker $i \in \{1, 2\}$ to be type $t_i \in \{s, g\}$ at the cost of h_{t_i} according to the chosen organizational type.

3. The local circumstances θ_i are realized, and worker i observes their own θ_i with probability $p_\theta^{t_i}$.

4. Worker i communicates with worker $j \in \{1, 2\}$ and $j \neq i$ to learn the primary action a_{jj} of their counterpart. While a generalist worker i can observe the primary action of worker j, a specialist worker i cannot observe the primary action of worker j.

5. For all $i, j \in \{1, 2\}$ and $i \neq j$, the worker responsible for task i chooses actions a_{ii} and a_{ij} to minimize the cost function.

Through the cost minimization problem of worker i, I derive the optimal organization compositions—S-S, G-G, or S-G—given the parameters. I then examine how these optimal compositions change as the parameters vary through comparative statics.

2.2 Costs by Organization Types

To derive organizational costs for each composition, I first analyze two individual cases: (1) the cost of worker 1 working with a specialist (worker 2), and (2) the cost of worker 1 working with a generalist (worker 2). I then calculate the total costs for each organizational composition by summing the costs for each case.

In the case where worker 1 works with a specialist, worker 1's cost function is $c_1 = \phi(a_{11} - \theta_1)^2 + \beta(a_{21} - a_{11})^2 + h_{t_1}$. As the counterpart is a specialist, the complementary action $a_{21}^* = 0$. If worker 1 can observe θ_1, the optimal problem is solved by the first-order condition $\frac{\partial c_1}{\partial a_{11}} = 0$. Thus, worker 1's optimal primary action $a_{11}^* = \frac{\phi}{\phi+\beta}\theta_1$. If worker 1 cannot observe θ_1, the primary action $a_{11}^* = E[\theta_1] = 0$. Therefore, the expected cost c_1 with a specialist is:

$$E[c_1|t_2 = s] = p_\theta^{t_1} \frac{\phi\beta}{\phi + \beta} \sigma_\theta^2 + (1 - p_\theta^{t_1}) \phi \sigma_\theta^2 + h_{t_1}$$

Next, consider the case where worker 1 works with a generalist. As the counterpart is a generalist and can perfectly coordinate with worker 1, the complementary action is $a_{21}^* = a_{11}$. If worker 1 can observe θ_1, the optimal problem is solved by $\frac{\partial c_1}{\partial a_{11}} = 2\phi(a_{11} - \theta_1) = 0$. Thus, the primary action $a_{11}^* = \theta_1$. If worker 1 cannot observe θ_1, $a_{11}^* = E[\theta_1] = 0$. Hence, the expected cost c_1 with a generalist is:

$$E[c_1|t_2 = g] = (1 - p_\theta^{t_1})\phi\sigma_\theta^2 + h_{t_1}$$

Table 1 summarizes worker 1's primary action a_{11}^*, worker 2's complementary action a_{21}^* and the corresponding costs when working with either a specialist or a generalist. Total organizational costs for each composition are calculated by summing the individual workers' costs:

$$E[C|t_1 = s, t_2 = s] = 2 * \text{(A)} = 2p_\theta^s \frac{\phi\beta}{\phi + \beta}\sigma_\theta^2 + 2(1 - p_\theta^s)\phi\sigma_\theta^2 + 2h_s \tag{2}$$

$$E[C|t_1 = s, t_2 = g] = \text{(A)} + \text{(B)} = p_\theta^g \frac{\phi\beta}{\phi + \beta}\sigma_\theta^2 + (2 - p_\theta^s - p_\theta^g)\phi\sigma_\theta^2 + h_s + h_g \tag{3}$$

$$E[C|t_1 = g, t_2 = g] = 2 * \text{(B)} = 2(1 - p_\theta^g)\phi\sigma_\theta^2 + 2h_g \tag{4}$$

Table 1: Summary of Actions and Costs

With (Worker 2):	1's primary action a_{11}^*	2's complementary action a_{21}^*	1's cost c_1	
S	$\begin{cases} \frac{\phi}{\phi+\beta}\theta_1 & (p_\theta^{t_1}) \\ 0 & (1 - p_\theta^{t_1}) \end{cases}$	0	$p_\theta^{t_i} \frac{\phi\beta}{\phi+\beta}\sigma_\theta^2 + (1 - p_\theta^{t_i})\phi\sigma_\theta^2 + h_{t_1}$	(A)
G	$\begin{cases} \theta_1 & (p_\theta^{t_1}) \\ 0 & (1 - p_\theta^{t_1}) \end{cases}$	a_{11}	$(1 - p_\theta^{t_1})\phi\sigma_\theta^2 + h_{t_1}$	(B)

The key takeaway is the difference in primary action a_{ii} depending on whether the counterpart is a specialist or a generalist. When the counterpart is a specialist, the specialist cannot observe worker i's primary action a_{ii}, and thus, cannot coordinate. Even though worker i can observe local information θ_i, the primary action a_{ii} must adjust to $\frac{\phi}{\phi+\beta}\theta_i$. This suggests that when working with a specialist, worker i sacrifices some adaptation to account for coordination loss and to minimize the cost function. In contrast, when the counterpart is a generalist, worker i can achieve perfect adaptation $a_{ii} = \theta_i$ if they observe local information, as a generalist can perfectly coordinate with a_{ii}. The counterpart type t_j and their complementary actions a_{ji} influence focal workers' primary actions a_{ii}, indicating that adaptation actions must be adjusted based on coordination results to minimize production costs. This model highlights the strengths and weaknesses of specialists and generalists, emphasizing the trade-off between adaptation and coordination.

2.3 Comparative Statics

In this subsection, I compare production costs across the organizational compositions S-S, S-G, and G-G, and present propositions on the optimal composition based on the model's parameters. By comparing the costs derived from Equations (2)-(4), I derive the conditions for the lowest-cost organizational composition:

S-S is the least costly organizational composition when

$$\frac{\beta}{\phi + \beta} \leq \frac{p_\theta^s - p_\theta^g}{2p_\theta^s - p_\theta^g} + \frac{h_g - h_s}{(2p_\theta^s - p_\theta^g)\phi\sigma_\theta^2}. \tag{5}$$

S-G is the least costly organizational composition when

$$\frac{p_\theta^s - p_\theta^g}{2p_\theta^s - p_\theta^g} + \frac{h_g - h_s}{(2p_\theta^s - p_\theta^g)\phi\sigma_\theta^2} \leq \frac{\beta}{\phi + \beta} \leq \frac{p_\theta^s - p_\theta^g}{p_\theta^g} + \frac{h_g - h_s}{p_\theta^g \phi\sigma_\theta^2}. \tag{6}$$

G-G is the least costly organizational composition when

$$\frac{p_\theta^s - p_\theta^g}{p_\theta^g} + \frac{h_g - h_s}{p_\theta^g \phi\sigma_\theta^2} \leq \frac{\beta}{\phi + \beta}. \tag{7}$$

The detailed calculation process is provided in Appendix A.1. To clarify these relationships, I define $SS(\phi, \sigma_\theta^2) \equiv \frac{p_\theta^s - p_\theta^g}{2p_\theta^s - p_\theta^g} + \frac{h_g - h_s}{(2p_\theta^s - p_\theta^g)\phi\sigma_\theta^2}$ and $GG(\phi, \sigma_\theta^2) \equiv \frac{p_\theta^s - p_\theta^g}{p_\theta^g} + \frac{h_g - h_s}{p_\theta^g \phi\sigma_\theta^2}$. I then state several propositions regarding the monotonicity in key parameters to predict the optimal organizational composition[11].

Proposition 1. *As the importance of coordination, β, increases, the organizational choice shifts from having more specialists to more generalists.*
Proof is straightforward from Equations (5)–(7) and is therefore omitted.

Proposition 2. *As uncertainty, σ_θ^2, increases, the organizational choice shifts from having more specialists to more generalists, provided that $\frac{\beta}{\phi+\beta} \geq \frac{p_\theta^s - p_\theta^g}{p_\theta^g}$.*
Proof is provided in Appendix A.4.

Proposition 1 indicates that higher coordination importance (β) leads to a generalist-oriented organization. A high β value suggests that coordination failures (i.e., $a_{ji} \neq a_{ii}$) severely damage the organization's profit. To minimize coordination losses, the organization assigns more generalists, who are better at coordinating with others.

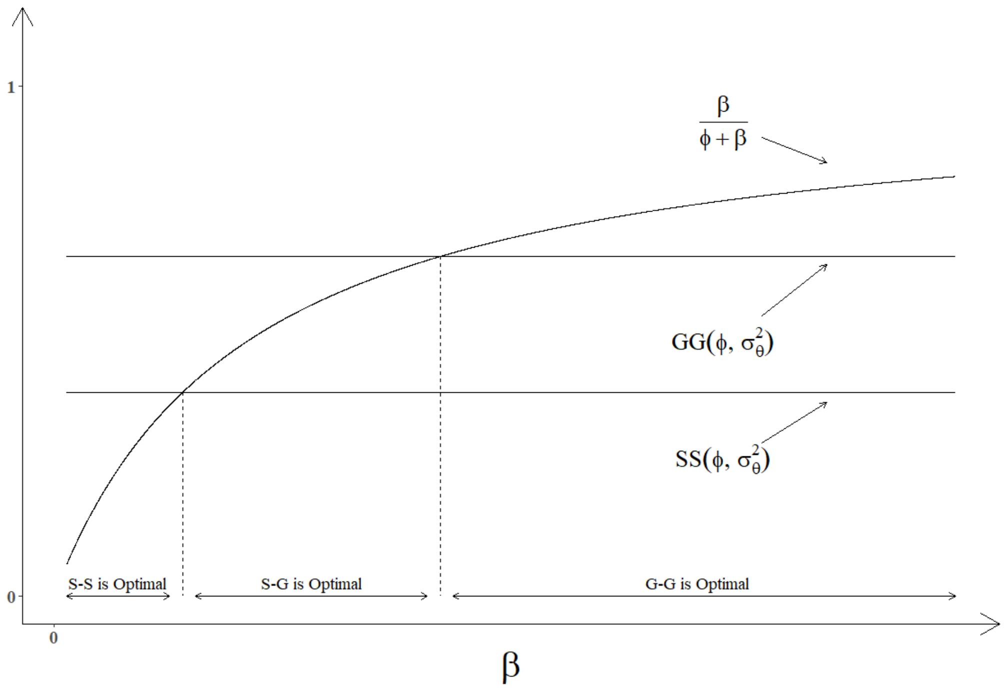
Figure 1 illustrates the relationship between expected costs and coordination across the three organizational compositions—S-S, S-G, and G-G—based on Equations (5)–(7). In this figure, both $SS(\phi, \sigma_\theta^2)$ and $GG(\phi, \sigma_\theta^2)$ are constants, as they do not include the coordination parameter β. This shows that as β increases, $\frac{\beta}{\phi+\beta}$ surpasses $SS(\phi, \sigma_\theta^2)$ and $GG(\phi, \sigma_\theta^2)$, making the G-G organization the least costly and optimal composition. The figure also highlights the threshold $GG(\phi, \sigma_\theta^2) < 1$, which is the condition that G-G can become the optimal organizational composition. This threshold condition does not affect monotonicity in β owing to the definition of monotonicity[12]. However, if $GG(\phi, \sigma_\theta^2) \geq 1$, the G-G composition cannot be optimal, even if β becomes extremely high, because $\frac{\beta}{\phi+\beta} < 1$.

The importance of coordination, relative to the importance of adaptation (ϕ), is reflected in $\frac{\beta}{\phi+\beta}$. Adaptation, therefore, shows a monotonous, inverse relationship with the optimal organizational structure. As the importance of adaptation increases, the optimal composition shifts from the one with many generalists to the one with many specialists. Organizations where market adaptation is crucial for profitability require more specialists, as they minimize adaptation losses more effectively than generalists. For a detailed discussion of monotonicity with respect to ϕ and the proof, see Appendix A.2.

Proposition 2 states that increased uncertainty in the local environment encourages the organization to favor generalists over specialists. In this model, uncertainty affects both adaptation and coordination losses, as the local information θ_i influences optimal primary actions a_{ii}^*. The monotonicity with respect to σ_θ^2 requires that the relative importance of coordination $\frac{\beta}{\phi+\beta}$ is sufficiently high (i.e., $\frac{\beta}{\phi+\beta} \geq \frac{p_\theta^s - p_\theta^g}{p_\theta^g}$) must hold. In other words, coordination losses must be more critical than adaptation losses in determining total organizational costs. This implies that generalists experience smaller losses than specialists owing to increased uncertainty. Therefore, when the importance of coordination is sufficiently high, the organizational composition shifts toward generalist-dominant as market uncertainty

[11] For other parameters, such as ϕ, $p_\theta^{t_i}$, and h_{t_i}, see Appendix A.2.
[12] See Definition 1 in Appendix A.4.

Figure 1: Relationship of Expected Costs in terms of Coordination across Three Organizational Compositions



increases[13]. If the condition $\frac{\beta}{\phi+\beta} \geq \frac{p_\theta^s - p_\theta^g}{p_\theta^g}$ is not satisfied, monotonicity does not hold, and the optimal composition either remains S-S or shifts to S-G, regardless of how large market uncertainty becomes.

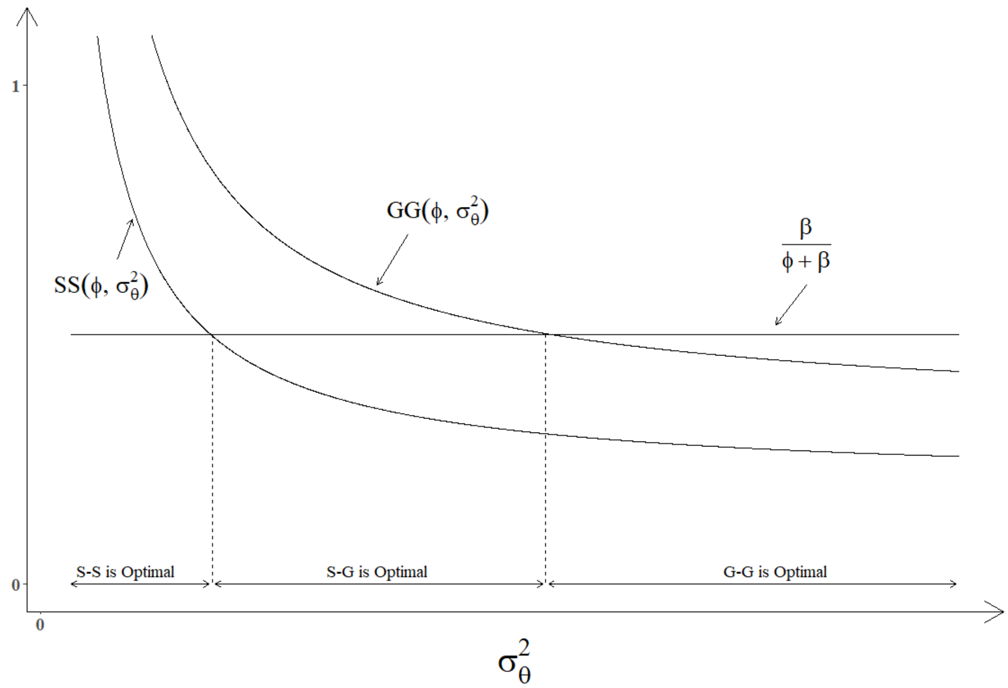
Figure 2 illustrates Proposition 2 based on the relations in Equations (5)-(7). The value of $\frac{\beta}{\phi+\beta}$ remains fixed, with the horizontal axis representing uncertainty σ_θ^2. Both $SS(\phi, \sigma_\theta^2)$ and $GG(\phi, \sigma_\theta^2)$ are decreasing functions with respect to σ_θ^2. As the uncertainty of local information rises, the optimal organizational structure transitions from S-S to S-G and then to the G-G[14].

The monotonicity in uncertainty σ_θ^2 implies that the complementarity between specialists and generalists in the S-G composition becomes more pronounced when uncertainty differs across tasks. Suppose that the uncertainty of local information for task 1 is lower than that for task 2, that is, $\sigma_{\theta_1}^2 < \sigma_{\theta_2}^2$ and Equation (6) holds. This model demonstrates that assigning a generalist to less uncertain task 1 and a specialist to more uncertain task 2 is more optimal than the reverse (for details, see Appendix A.3). This suggests that specialists and generalists should be assigned to tasks based on the

[13]This finding appears to contradict DeVaro and Farnham (2011) and DeVaro and Gürtler (2016), which suggest that greater market volatility leads to greater specialization. However, the volatility in their study refers to the variance in "innovation required to meet the demanded product specifications"(DeVaro and Farnham, 2011, p.864), reflected in the product price. They assume that multiskilled workers are unable to produce the product when the requirement is sufficiently high. DeVaro and Farnham (2011) distinguish between product innovation (adapting a product to market changes) and process innovation, clarifying that they focus on the former. Given this, I interpret their concept of volatility as aligning with the importance of adaptation in this study, making my findings consistent with DeVaro and Farnham (2011) and DeVaro and Gürtler (2016).

[14]The assumption that $h_g > h_s$ is critical for proposition 2. When the assumption flips, that is, $h_g < h_s$, this results in reverse monotonicity: optimal composition shifts from generalist-only to specialist-only as uncertainty increases if the condition $\frac{\beta}{\phi+\beta} \leq \frac{p_\theta^s - p_\theta^g}{p_\theta^s}$ holds—in other words, when the importance of coordination is significantly low. As illustrated in Table A.2, $SS(\phi, \sigma_\theta^2)$ and $GG(\phi, \sigma_\theta^2)$ are increasing functions in σ_θ^2, as $\frac{h_g - h_s}{\phi \sigma_\theta^2}$ is negative. As noted in Section 2, I assume that the Japanese trading company used in the empirical analysis in this paper typically trains workers through on-the-job training and job rotation, and that rotating workers to become generalists is costly for organizations. Therefore, I focus on the case where $h_g > h_s$.

Figure 2: Relationship of Expected Costs in terms of Uncertainty Across Three Organizational Compositions



relative levels of uncertainty when a balanced composition is optimal.

2.4 Empirical Prediction

Building on Propositions 1 and 2, I hypothesize empirically within the context of organizations with varying circumstances.

Prediction 1. *Organizations that prioritize coordination (relative to adaptation) will have a higher proportion of generalists than those that place less emphasis on coordination.*

Prediction 2. *Gven that coordination is sufficiently important, organizations facing higher market uncertainty will have a higher proportion of generalists than those facing lower uncertainty.*

3 Data

To test the predictions regarding optimal organizational compositions, I use personnel data from a large general trading company in Japan, here referred to as J-Trading. J-Trading operates in various business fields, both domestically and internationally. The firm's primary business can be categorized into two types: commodity trading and business investment. Commodity trading serves as an intermediary, connecting demanders and suppliers of products. In contrast, business investment involves generating profit by investing firms, aiming to enhance the corporate value of investees and foster synergies between J-Trading and these firms through management resources, including human resources, capital, information, and expertise. J-Trading's business fields can be grouped into seven main areas: Consumer Business, Infrastructure, Energy, Agriculture, Machinery, Chemicals, and Metals. Machinery, Chemicals, and Metals are classified under commodity trading, as they primarily handle and trade products within their respective fields. Consumer Business, Infrastructure, Energy, and Agriculture focus on business investment, managing project-based ventures[15].

The personnel dataset includes employee attributes, such as age, gender, family status, job tenure, job grade, and job position, for each assignment. To track employees' careers and specialization, I used assignment history records detailing workplaces, divisions, and the corresponding dates for each assignment. These records provide a comprehensive view of each employee's career from entry to retirement. The dataset covers all J-Trading's employees from their hiring through the fiscal year 2023, including those who resigned or retired during this period.

For this analysis, I restricted the sample to the following. First, I included only regular employees, as these individuals are expected to be transferred across business areas by the company and potentially assigned overseas for career development. Second, I focused on employees working in one of the business areas as of fiscal year 2023 to compare specialization levels across the seven areas. Third, I limited the sample to employees with more than 10 years of tenure at J-Trading. Younger employees, such as new graduates, have inherently experienced fewer business areas than senior employees. Categorizing younger employees with limited experience as "specialists" would be inappropriate, as they expected to gain broader experience over time. Thus, employees with more than ten years of service are considered suitable for this analysis[16]. Fourth, I restrict the sample to regular employees who joined J-Trading in 1984 or later as new university graduates, assuming they will reach the official retirement age of 60 by 2022. This allows me to capture detailed career path information while excluding older workers. Finally, this study uses individual-level data, with the unit of observation being individual workers and their career paths, measured by complete assignment information from their entry to J-Trading through fiscal year 2023. Therefore, the data is cross-sectional.

I use Market Beta as a proxy for uncertainty in each business area. Market Beta, commonly used in finance, indicates a stock's sensitivity to overall market movements. Market Beta is was originally used as a measure of a stock's risk in a capital asset pricing model built by Sharpe (1964) and Mossin (1966), and is continuously used in empirical research for risk parameters[17]. It represents the percentage change in a stock's return for a 1% change in the stock market. A higher Market Beta means a stock is more sensitive to market fluctuations with high risk, implying greater uncertainty in the associated business area. I determined the mean Market Beta for industries linked to J-Trading's seven business areas by using the average Market Beta over the past 60 months (through May 2024) for 33 industries listed on the Tokyo Stock Exchange[18].

4 Measuring Specialization

4.1 Number of Experienced Business Areas

To measure career specialization, I first calculate the total number of business areas each employee has experienced throughout their career. The assignment records contain information on the workplaces, departments, and divisions where employees have worked since joining J-Trading. I categorize each workplace and department into one of J-Trading's seven main business areas: Consumer Business,

[15]Agriculture and Machinery have both business investment and commodity trading aspects but are categorized based on the distinction between their project-based or product-based activities

[16]This analysis includes employees hired as new graduates and through mid-career recruitment because of difficulty in clearly distinguishing between them in the dataset. Japanese companies, including J-Trading, typically recruit new graduates and train them internally. Data shows that approximately 80% of employees who joined J-Trading were aged between 22 and 26, making employees with over 10 years of service representative of those with most of their career at J-Trading.

[17]For example, the difference in time-varying risk between growth and value stocks (Petkova and Zhang, 2005), the relationship between Beta uncertainty and stock returns (Hollstein, Prokopczuk, and Wese Simen, 2020), the effect of beta uncertainty in the oil market on the stock market (Chen and Demirer, 2022), and decomposition of Beta into cash-flow Beta and discount rate Beta to reflect investors' attitudes (Campbell and Vuolteenaho, 2004).

[18]Data is sourced from https://costofcapital.jp/ with permission. (In Japanese.)

Infrastructure, Energy, Agriculture, Machinery, Chemicals, and Metals[19]. Some past departments cannot be categorized into the current seven business areas. I classify these as "others" and add 1 to the total number of experienced business areas for any employee who has worked in such a department, regardless of the number of times. Employees currently assigned to a business area but with prior experience in corporate departments (e.g., human resource management and accounting) will also have 1 added to their total, irrespective of the frequency of assignment. Therefore, the maximum number of experienced business areas is 9.

Using the total number of experienced business areas, I create four measures of specialization. The first measure is the total number of experienced business areas for each worker, which reflects the breadth of experience. A higher average in a given business area suggests a greater proportion of generalists within that area. The second measure is a dummy variable indicating whether an employee has worked in only one business area, identifying specialists who focus solely on one area. The third measure is a dummy variable for employees with experience in up to two business areas, identifying broader specialists. I use these dummy variables to calculate and compare the proportion of specialists across the seven business areas. Finally, to capture the depth of experience in a specific business area, I calculate the proportion of time an employee has spent in their current business area relative to their entire career at J-Trading as of fiscal year 2023. This indicator measures expertise based on the length of experience, complementing the frequency of transfers across areas.

4.2 Intensity of Career

The assignment history includes valuable qualitative data, such as division and department names. To measure specialization further, I employ Latent Dirichlet Allocation (LDA), an unsupervised machine learning algorithm (Blei et al., 2003). LDA is a hierarchical Bayesian factor model originally used to reduce the dimensionality of data and identify the latent topics. Recently, it has been applied in economics literature to capture CEO behavior, using time-use surveys of CEOs' diaries (Bandiera et al., 2020; Englmaier et al., 2023). I apply LDA to conduct text analysis by treating the list of all divisions, departments, and workplaces experienced by each employee as a single document[20].

LDA estimates two distributions based on word occurrence: the first is the topic distribution over documents, indicating the weight of each topic within a document. In my analysis, reducing the dimensionality of career data allows me to observe the contribution rate of each N career topic that constitutes an employee's career. The second distribution is the word distribution over topics, which gives the probability of word occurrences for each topic. In this study, it helps identify which career-related words (i.e., job information included in division and department names) are most likely to appear in each topic[21].

One advantage of LDA is its probabilistic classification, which is non-deterministic (Englmaier et al., 2023). It provides a topic distribution for each document, indicating the extent to which each career topic contributes to the worker's career. As employees may transfer across multiple business areas, it would be inappropriate to classify a career trajectory with a single label. Instead, LDA enables a more nuanced interpretation of specialization versus generalization based on the intensity of various topics that constitute the worker's career. While other probabilistic classifiers, such as principal component analysis and factor analysis, assume normally distributed data (Tipping and Bishop, 1999), the data used to measure career specialization—particularly the word co-occurrence matrix—are unlikely to follow a Gaussian distribution. Thus, LDA is more suitable for this type of data.

[19] J-Trading occasionally undergoes organizational reforms, resulting in department name changes. However, most departments can be linked to one of the current seven business areas, or their functions are inherited by J-Trading subsidiaries. Thus, I can generally categorize past departments into one of these areas. Additionally, LDA, using text assignment history data (described in the next subsection), could address concerns related to organizational reforms.

[20] In the LDA analysis, the data include the assignment histories of regular employees who joined the company in 1984 or later and are working not only in business areas but also in corporate divisions as of 2023, regardless of tenure, in order to capture overall career-related topics.

[21] Due to the anonymity of J-Trading, specific frequent words in each topic are not shown in this paper.

Given that the assignment records are written in Japanese, a language without spaces between words, I first decompose the Japanese department names into basic terms. Using MeCab, a tool for Japanese morphological analysis (Kudo, Yamamoto, and Matsumoto, 2004) and the Unidic segmentation dictionary (Den, Ogiso, Ogura, Yamada, Minematsu, Uchimoto, and Koiso, 2007). This analysis generates a document-term matrix, where each row represents a document (employee's assignment history), and each column represents the frequency of term occurrences.

4.3 Determining the Number of Career Topics

In LDA, researchers must specify the number of latent topics to estimate. Both Bandiera et al. (2020) and Englmaier et al. (2023) selected two topics, with Englmaier et al. (2023) explaining that a lower number of topics enhances interpretability while maintaining flexibility. In this study, I determine the number of topics based on two commonly used measurements for LDA analysis: perplexity and coherence. Perplexity measures the prediction accuracy of word occurrences in test data, given the LDA results from the training data. Specifically, it calculates the inverse of the geometric mean per-word likelihood, as described by the following equation (Blei et al., 2003, p.1008):

$$perplexity(D_{test}) = \exp\left\{-\frac{\sum_{d=1}^{M}\log p(\boldsymbol{w}_d)}{\sum_{d=1}^{M} N_d}\right\},$$

where d represents a document, N_d is the total number of words in document d, and $\boldsymbol{w}_d$ is the vector of words in document d. A lower perplexity score indicates better predictive performance.

Coherence, in turn, measures the interpretability of a topic, based on the clustering of words with similar meanings. Various methods for calculating word similarity exist, and in this study, I follow Röder, Both, and Hinneburg (2015), who identified the method most strongly correlated with human ratings. The core idea behind word similarity is *pointwise mutual information* (PMI), which calculates the co-occurrence frequency between pairs of words. These counts are derived from a sliding window applied to the document. The equation is as follows:

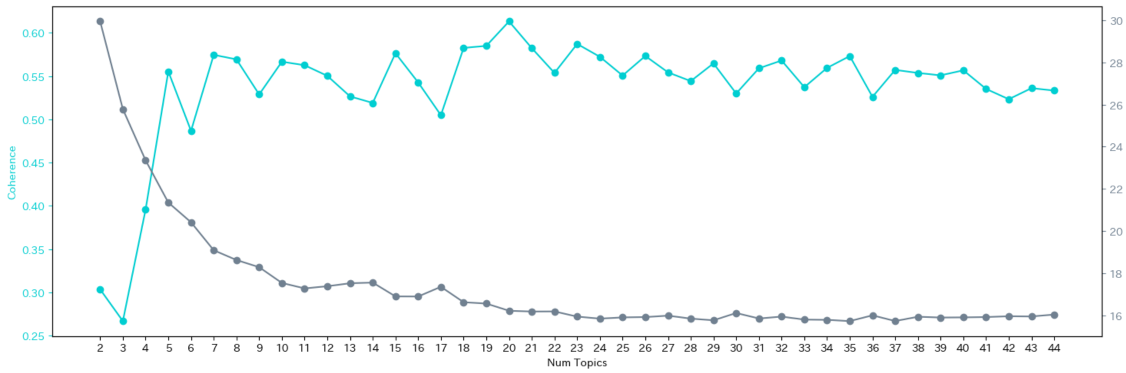
$$PMI(w_i, w_j) = \log\frac{p(w_i, w_j) + \epsilon}{p(w_i) \cdot p(w_j)},$$

where ϵ is a small constant to avoid the logarithm of zero. If the words are independent, then $p(w_i, w_j) = p(w_i) \cdot p(w_j)$, resulting in a PMI score of zero. A positive PMI score, $PMI(w_i w_j) > 0$, indicates that words w_i and w_j are more likely to co-occur, while a negative PMI score, $PMI(w_i w_j) < 0$, suggests that they are less likely to co-occur. In this study, I adopt the C_V method, which Röder et al. (2015) found to have the strongest correlation with human ratings. In this method, PMI is normalized by dividing $PMI(w_i w_j)$ by $-\log(p(w_i, w_j) + \epsilon)$ and the coherence score is derived by computing the cosine similarity of the vector of PMI scores for top N words in each topic for each document. The arithmetic mean of these cosine similarities yields the final score[22]. In this study, I set the number of top words to 10 and the window size to 15 words for the coherence test.

Figure 3 presents the results for perplexity and coherence. A lower perplexity score and a higher coherence score indicate better performance in prediction accuracy and ease of interpretation, respectively. The graph shows that the perplexity score decreases as the number of topics increases, while the coherence score fluctuates as the number of topics grows. Based on these results, I selected 20 topics, which exhibited the highest coherence and a low perplexity score. I also perform a robustness check by varying the number of topics, with consistent results presented in Section 6.

[22] Röder et al. (2015) noted that using cosine similarity, rather than direct word probability, better captures words that semantically support each other, even if they do not frequently co-occur. A detailed explanation can be found in Röder et al. (2015).

Figure 3: Results of Perplexity and Coherence



4.4 Calculation of Specialization

To measure specialization, I use the Herfindahl-Hirschman index (HHI) to calculate the intensity of the career topic vector. Suppose the number of topics is 20, and the vector of career topics for worker i is denoted as $\boldsymbol{\Omega}_i = (\omega_{i1}, \omega_{i2}, ..., \omega_{i20})$. The equation for specialization for individual workers based on HHI in this study is as follows:

$$CareerHHI_i = \sum_{\rho} \omega_{i\rho}^2$$

where $\omega_{i\rho}$ represents the contribution rate of topic ρ for worker i. The HHI is derived from the sum of the squared contribution rates of each topic and reflects the intensity of a worker's career topics. A higher value of $CareerHHI_i$ indicates greater intensity in a specific topic ρ, suggesting the worker is more specialized in that area. I then calculate the arithmetic mean of $CareerHHI_i$ for each business area to assess the level of specialization within business areas.

The career HHI outperforms the other four specialization indices at the business area level in capturing worker specialization. The career topics estimated by LDA incorporate detailed text information from employee assignment history, including divisions, departments, and sections. This allows the career HHI to account for job rotation within and across business areas as well as organizational name changes, providing a more accurate measure of career specialization. Therefore, I consider career intensity the most important index among the five.

4.5 Summary Statistics

Table 2 presents the summary statistics for employee attributes and the ratio of employees across business areas. Panel A shows that the average age and tenure are relatively high, as expected, given the restriction to workers with more than 10 years of tenure. The data also indicate that the proportion of female workers is quite low. This can be attributed to the fact that large Japanese firms like J-Trading, which are typically male-dominated, with fewer female workers remaining in long-term employment, owing to life events such as marriage and childcare. Regarding the proportion of workers across business areas, Chemicals has the highest number of workers, while Infrastructure has the fewest. The Market Beta appears higher in commodity trading areas than in business investment areas.

Table 2 also shows summary statistics for the specialization index. The mean career HHI is over 0.5, suggesting that workers in business areas tend to specialize in one or two career topics on average. The average number of experienced business areas for workers is 2.5. Additionally, the proportion of specialists—those with experience in only one business area—is 15.6%. This indicates that few workers specialize in a single area, and many take on multiple roles throughout their careers. The fact that half of the workers have experience in at most two business areas further supports the observation that many employees hold multiple roles during their careers. Figure 4 illustrates the kernel density

Table 2: Summary Statistics of Employee Attributes

Panel A: Attributes

	N	mean	sdv	min	max
Age	660	47.96	7.182	32	60
Tenure	660	22.76	7.493	10	38
Female Dummy	660	0.048	0.215	0	1
Married Dummy	660	0.911	0.286	0	1
Postgraduate Dummy	660	0.121	0.327	0	1
Manager Dummy	660	0.774	0.418	0	1
Career HHI	660	0.588	0.230	0.180	0.993
# of Exp Divs	660	2.530	1.071	1	6
Only one Exp Area Dummy	660	0.156	0.363	0	1
Up to two Exp Areas Dummy	660	0.547	0.498	0	1
Career Ratio of the Latest Area	660	0.626	0.283	0.015	0.999

Panel B: Business Areas

	N	Ratio (%)	Market Beta
Business Investment:			
Consumer Business	105	15.91	0.995
Infrastucture	50	7.58	1.258
Energy	111	16.82	0.866
Agriculture	106	16.06	0.770
Commodity Trading:			
Machinery	63	9.55	1.155
Chemicals	125	18.94	1.050
Metals	100	15.15	1.453

The unit of observation is individual workers. The sample is restricted to regular employees who are currently employed in a business area, have more than 10 years of tenure, and have not left the firm as of FY 2023. The employees used to estimate career topics via LDA include all those who joined J-Trading after fiscal year 1984, allowing for the capture of career trajectories across all regular employees.

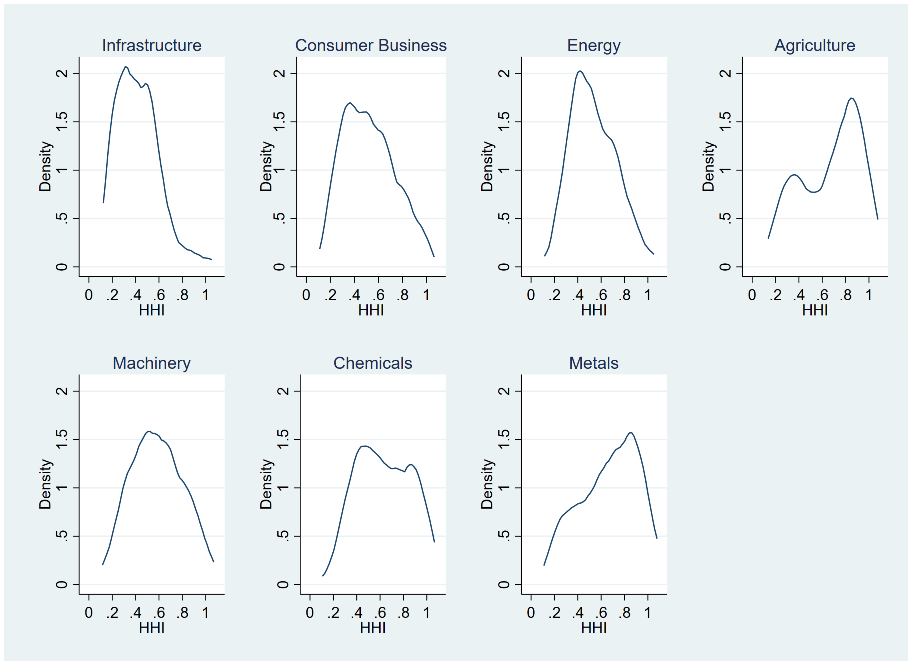
distributions of career HHI and the total number of experienced business areas. The distributions of the total number of experienced areas appear uneven, probably owing to their discrete number but bell shape. At the same time, the distributions of career HHI also show that, although the average and median are different among the business areas, most distributions follow a bell curve except for Agriculture. This suggests that these averages reflect the degree of specialization within each business area.

5 Empirical Strategy

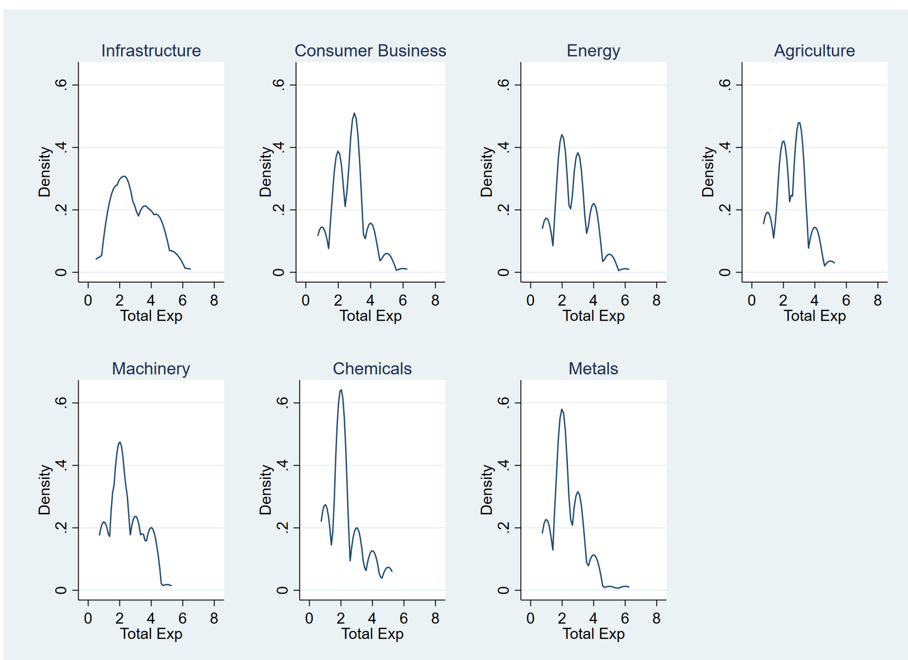
In Section 2, I outlined the empirical predictions regarding the composition of specialists and generalists within an organization, based on coordination, adaptation, and uncertainty. I form empirical hypotheses based on differences in coordination and adaptation characteristics between the commodity trading and business investment areas at J-Trading.

To understand these characteristics, I conducted interviews with managers at J-Trading. In October 2023, I spoke with two managers in the Consumer Business area, a business investment division, and in January 2024, I interviewed two managers in the Chemicals area, a commodity trading division. The interview revealed that the Consumer Business area holds more frequent meetings, including weekly gatherings among managers and directors within the area and daily meetings with employees transferred to overseas investee firms for information sharing and business procedure review. In con-

Figure 4: Distribution of Specialization Among Business Areas



Panel A: Career HHI



Panel B: The total number of experienced business areas trast, the Chemicals area managers emphasized the importance of product knowledge, compliance through employee training (particularly with hazardous chemicals), and inventory management to ensure product delivery to customers rather than for speculative purposes. They are also adopting digitalization to optimize product stock and quality control. A key distinction between the two areas is that Consumer Business focuses on communication and information sharing within the area, while Chemicals emphasizes products and market knowledge. This suggests that coordination is more critical in business investment areas, while adaptation is more important in commodity trading areas.

To test the consistency of these empirical predictions with the actual firm data, I formulate the following two empirical hypotheses based on the above discussion[23]:

1. Divisions in commodity trading areas have more specialists than divisions in business investment areas with their greater need for adaptation to market conditions.

2. The proportion of specialists in business investment divisions, with their greater need for coordination, is negatively associated with Market Beta.

First, I present descriptive results for the hypotheses using the means of specialization indices and Market Beta. Then, I estimate the following equations with individual attributes as control variables:

$$Y_i = \alpha_0 + \sum_{\tau} \alpha_\tau D_{i\tau} + \gamma \boldsymbol{X}_i + \varepsilon_i \tag{8}$$

$$Y_i = \alpha_0 + \mu_1 \sum_{\tau} D_{i\tau} Inv_\tau * Beta_\tau + \mu_2 \sum_{\tau} D_{i\tau} Inv_\tau + \mu_3 \sum_{\tau} D_{i\tau} Beta_\tau + \gamma \boldsymbol{X}_i + \varepsilon_i \tag{9}$$

where Y_i represents each specialization index for worker i, such as Career HHI, the total number of business areas experienced, a dummy variable indicating whether an employee has experience in only one business area, a dummy variable for experience in up to two business areas, or the proportion of the assignment period spent in the current business area. α_0 is a constant term. In Equation (8), $D_{i\tau}$ is a dummy variable indicating that worker i is assigned to business area τ, excluding one reference area (Consumer Business). $\boldsymbol{X}_i$ is a vector of control variables, including worker i's age, job tenure, and the fiscal year of the most recent transfer. I also control for attributes such as gender, postgraduate education, marriage status, and managerial position. As this is an individual-level analysis, selection bias, where some factors affect both specialization and business area dummy variables, should be considered. For example, many employees aspire to move to popular divisions from the current different divisions, which may result in their generalization. Thus, it is important to control employee attributes as much as possible. The coefficient of interest to examine the first hypothesis is α_τ, which represents the relationship between business area type (business investment or commodity trading) and a specialization index after controlling for worker attributes.

Equation (9) is the estimation for the second hypothesis. Inv_τ is a dummy variable indicating 1 if business area τ is categorized as a business investment area and $Beta_\tau$ is Market Beta for business area τ. The inclusion of the interaction of the two allows me to examine whether business investment divisions with higher market uncertainty have fewer specialists. Other variables are the same as Equation (8).

6 Results and Discussion

6.1 Descriptive Results

Figures 5 and 6 compare specialization across business areas using two distinct measurements. In each panel, the blue bars represent business investment areas, while the red bars represent commodity

[23] In the second hypothesis, commodity trading areas, where coordination is relatively less important, are expected to exhibit either no correlation while maintaining a high specialist ratio, or a weak negative correlation between Market Beta and specialization. This expectation is based on the model result that the optimal composition remains S-S or shifts to S-G, regardless of how large the uncertainty becomes, if the condition $\frac{\beta}{\phi+\beta} \geq \frac{p_\theta^s - p_\theta^g}{p_\theta^g}$ is not satisfied.

trading areas[24].

In terms of career HHI, Panel A of Figure 5 shows that business investment areas generally exhibit lower values than commodity trading areas. Notably, Infrastructure has a significantly lower HHI compared to Machinery, Chemicals, and Metals, indicating that employees in business investment areas tend to have broader experience. These findings support the first hypothesis outlined in Section 5. However, Agriculture, a business investment area, has the highest career HHI, which can be attributed to market uncertainty factors.

Panel B of Figure 5 presents a scatter plot of Market Beta versus mean career HHI. The blue-circled area represents business investment areas, while the red-circled area represents commodity trading areas. Business investment areas exhibit a downward trend in HHI as Market Beta increases, while commodity trading areas remain relatively flat. This suggests that higher market uncertainty is associated with less specialization in business investment areas, where coordination needs are supposed to be high. Agriculture experiences low uncertainty and demands higher specialization despite its coordination requirements for business investment. These findings align with the second hypothesis.

The comparison of the number of experienced business areas, as shown in Figure 6, follows a similar pattern. Specifically, Panel A shows that the average number of experienced areas in the commodity trading areas is lower than those in business investment areas, with Metals exhibiting a particularly low value compared to that of Infrastructure. These findings suggest that commodity trading areas tend to have relatively more specialists than business investment areas. The scatter plot further indicates that the mean number of experienced areas in business investment areas is positively correlated with Market Beta, whereas commodity trading areas show no such trend.

Other variables, such as the proportion of employees with experience in only one business area, those with experience in up to two business areas, and the career ratio within the current business area, reveal similar patterns. (see Appendix A.7.)

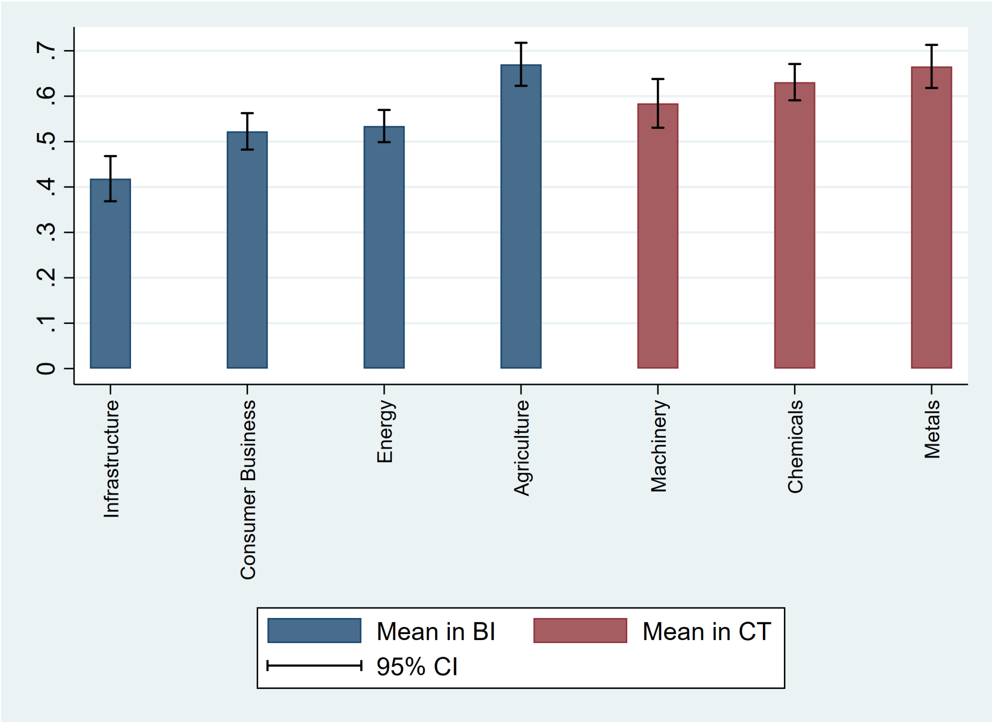
6.2 Estimation Results

Table 3 presents the estimation results for career HHI and the total number of experienced business areas. The reference category for the business area dummy variables is Consumer Business, a business investment area. Columns (1)-(3) report the results for career HHI. These results remain consistent, regardless of whether only basic attributes or all worker attributes are controlled. Among commodity trading areas, all except Machinery exhibit significantly positive coefficients. In contrast, the coefficient for Infrastructure, a business investment area, is significantly negative. This suggests that Infrastructure may require more coordination, leading to a higher proportion of generalists. The positive correlation between Agriculture and career HHI may likely stem from the low market uncertainty, as indicated by Market Beta. These findings support the conclusion that commodity trading areas tend to have more specialists than those in the business investment areas when career intensity is measured using machine-learning methods using assignment text data. These results are consistent with the model of Dessein and Santos (2006), suggesting that as the importance of coordination increases, organizations adapting to market conditions tend to have flexible employees through broad task assignments.

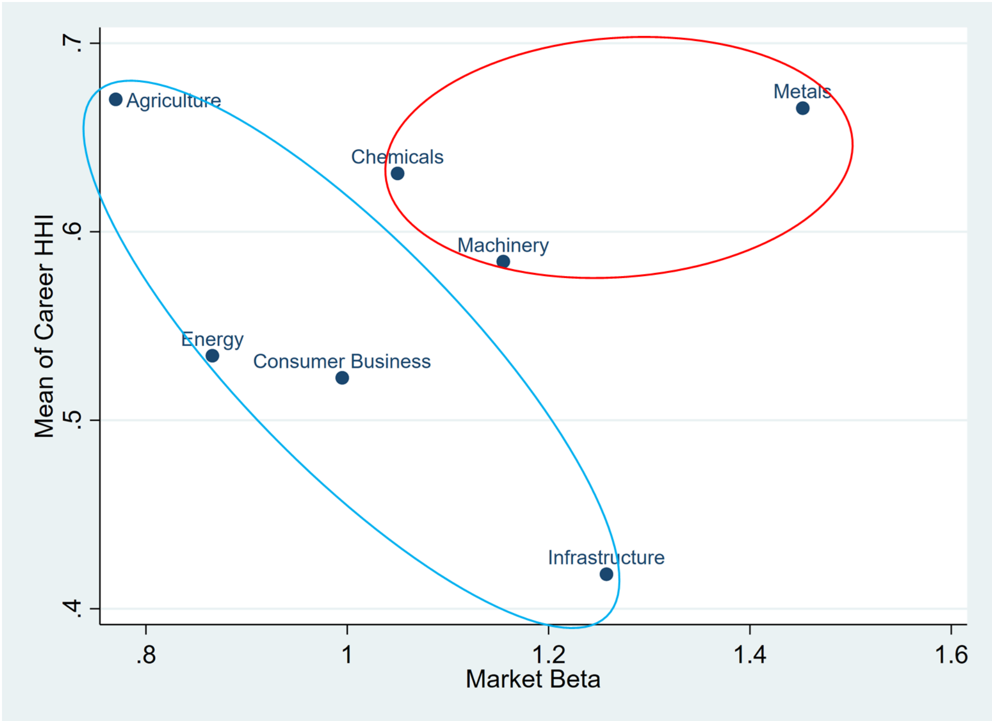
Columns (4)-(6) display the results for the total number of experienced business areas. As with the career HHI estimation, the results remain largely unchanged even after controlling for all worker attributes. The coefficients for Chemicals and Metals are negative compared to Consumer Business at the 5% significance level, indicating that employees in these commodity trading areas tend to have fewer experienced business areas than those in Consumer Business. Conversely, the coefficients for Infrastructure and Energy, both business investment areas, are insignificant but positive, suggesting that workers in these areas are either more slightly generalized or do not differ from those in other business investment areas.

[24] As described in Section 3, business investment areas include Infrastructure, Consumer Service, Energy, and Agriculture, while the commodity trading areas include Machinery, Chemicals, and Metals.

Figure 5: Comparing Specialization among Business Areas (Career HHI)

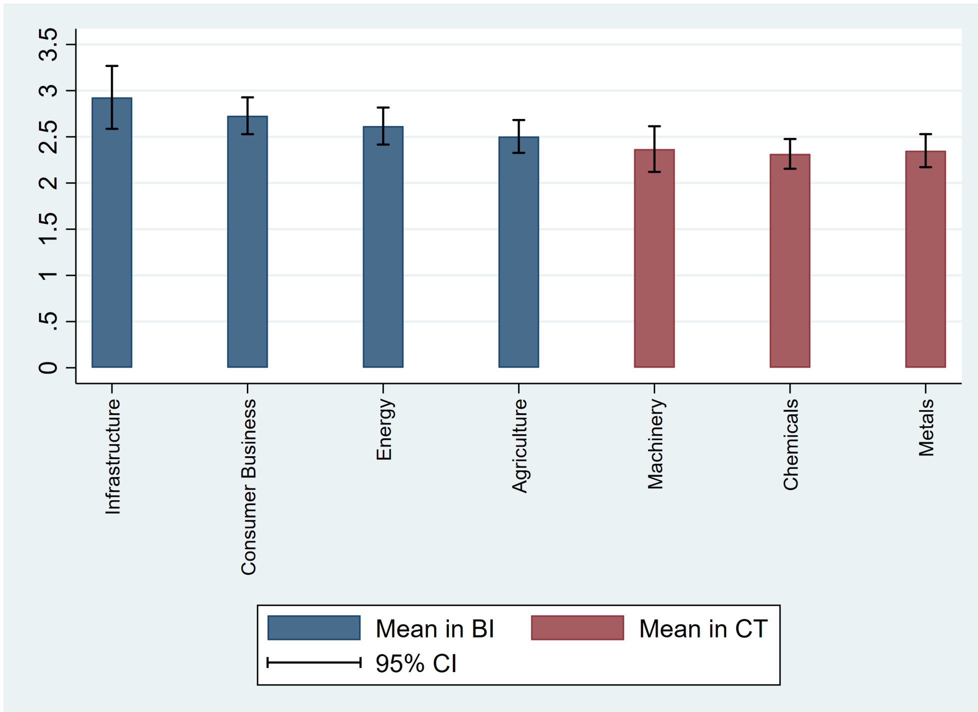


Panel A: Averages

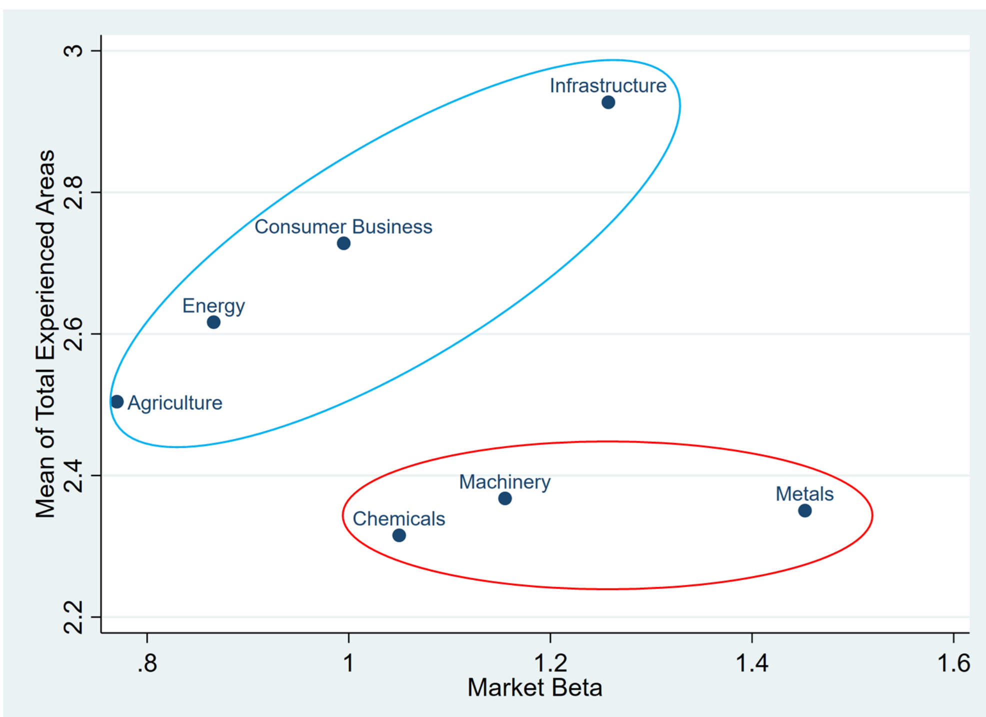


Panel B: A Scatter plot between specialization and market uncertainty

Figure 6: Comparing Specialization among Business Areas (The Number of Experienced Areas)



Panel A: Averages



Panel B: A Scatter plot between specialization and market uncertainty

Table 3: Estimation Results on Career Specialization and Business Areas

	(1) Career HHI	(2) Career HHI	(3) Career HHI	(4) Total Exp.	(5) Total Exp.	(6) Total Exp.
Business Investment:						
Consumer Business (Reference)						
Infrastructure	-0.102***	-0.095***	-0.095***	0.293	0.291	0.290
	(0.031)	(0.032)	(0.032)	(0.191)	(0.194)	(0.194)
Energy	0.013	0.015	0.015	0.059	0.059	0.059
	(0.027)	(0.027)	(0.027)	(0.141)	(0.142)	(0.143)
Agriculture	0.156***	0.159***	0.159***	-0.203	-0.204	-0.203
	(0.032)	(0.032)	(0.032)	(0.137)	(0.138)	(0.138)
Commodity Trading:						
Machinery	0.053	0.055	0.055	-0.213	-0.210	-0.211
	(0.034)	(0.034)	(0.034)	(0.158)	(0.158)	(0.158)
Chemicals	0.103***	0.103***	0.104***	-0.318**	-0.320**	-0.321**
	(0.029)	(0.029)	(0.029)	(0.135)	(0.135)	(0.136)
Metals	0.145***	0.144***	0.144***	-0.298**	-0.298**	-0.297**
	(0.032)	(0.032)	(0.032)	(0.135)	(0.136)	(0.136)
Base Controls	✓	✓	✓	✓	✓	✓
+Female, Education and Marriage		✓	✓		✓	✓
+Managerial Position			✓			✓
Constant	0.395***	0.345***	0.375***	3.159***	3.167***	3.110***
	(0.080)	(0.082)	(0.095)	(0.324)	(0.350)	(0.410)
Adjusted R^2	0.106	0.109	0.108	0.148	0.145	0.143
# of obs	660	660	660	660	660	660

Robust standard errors are in parentheses.
Base controls include age, tenure, and the fiscal year of the most recent transfer.
*** p<0.01, ** p<0.5, * p<0.1.

Table 4 presents the estimation results for the relationship between career specialization and market uncertainty. Columns (1)-(3) report the results for career HHI, while Columns (4)-(6) report those for the total number of experiences. In the case of career HHI, the coefficients for the interaction between the business investment dummy and Market Beta are significantly negative in all estimations. Similarly, all estimations for the total number of experiences exhibit positive significance at the 10% level. These imply that after controlling for employee attributes, as market uncertainty increases, divisions in business investment areas have a greater proportion of generalists.

6.3 Robustness Checks

To assess the robustness of my results, I estimated the model using alternative specialization indices as dependent variables: a dummy variable indicating that a worker has experienced only one business area, a dummy variable indicating that the total number of experiences is up to two areas, and the proportion of the worker's current business area relative to their entire career in J-Trading.

Columns (1) and (2) in Table 5 present the results for workers with experience in only one business area. The results in Column (1) show no significant findings except for Chemicals, which is significant at the 10% level. This may be owing to the low proportion of specialists who have experience in only one business area, resulting in unclear differences in ratios. Column (2) shows the relationship between specialization and the interaction term of the business investment dummy and Market Beta. The coefficients are negative but insignificant. Columns (3) and (4) examine those with experience in up to two business areas. In Column (3), the coefficients for the Chemicals and Metals are significantly higher than for Consumer Business, suggesting that the ratio of specialists, although broadly defined, is higher in commodity trading than in business investment areas. The coefficient for Machinery is significant at the 10% level, with a point estimate higher than those for the other business investment areas. Column (4) reports the results for the interaction term, showing an insignificant but positive

Table 4: Estimation Results on Career Specialization and Uncertainty

	(1) Career HHI	(2) Career HHI	(3) Career HHI	(4) Total Exp.	(5) Total Exp.	(6) Total Exp.
Business Investment * Market Beta	-0.621***	-0.611***	-0.608***	0.861*	0.854*	0.848*
	(0.103)	(0.104)	(0.104)	(0.485)	(0.490)	(0.492)
Business Investment	0.538***	0.530***	0.526***	-0.503	-0.497	-0.490
	(0.116)	(0.116)	(0.116)	(0.524)	(0.528)	(0.530)
Market Beta	0.129*	0.125	0.123	0.012	0.015	0.018
	(0.078)	(0.079)	(0.079)	(0.312)	(0.314)	(0.315)
Base Controls	✓	✓	✓	✓	✓	✓
+Female, Education and Marriage		✓	✓		✓	✓
+Managerial Position			✓			✓
Constant	0.347***	0.303***	0.333***	2.877***	2.885***	3.039***
	(0.116)	(0.117)	(0.128)	(0.438)	(0.445)	(0.557)
Adjusted R^2	0.090	0.093	0.092	0.148	0.145	0.143
# of obs	660	660	660	660	660	660

Robust standard errors are in parentheses.
Base controls include age, tenure, and the fiscal year of the most recent transfer.
*** p<0.01, ** p<0.5, * p<0.1.

coefficient[25].

Columns (5) and (6) present the results where the explained variable is the career proportion of the business area to which the worker currently belongs, relative to their entire career in J-Trading. As in previous columns, the results are clear. The coefficients for all commodity trading areas—Machinery, Chemicals, and Metals—are significantly positive at the 1% level. Although the coefficient for Agriculture is also significantly positive, its point estimate is lower than for the three commodity trading areas. In Column (6), the interaction term between the business investment dummy and Market Beta exhibits a significantly positive coefficient, consistent with the results in Table 3.

Additionally, I checked the robustness of the LDA results by varying the number of career topics to 15 and 25, applying the same descriptive analysis and estimation. The significance levels of some coefficients for business category dummy variables differ from those in Table 3, but the results remain consistent: commodity trading divisions have more specialists than business investment areas, and the proportion of specialists among business investment areas is lower in those with higher Market Beta (see Figures A.6 and A.7 and Tables A.2 and A.3 for details)[26].

7 Conclusion

This paper investigates the optimal organizational composition of employees with heterogeneous characteristics. In the context of organizational economics, the optimal structure is analyzed through two key actions: adaptation and coordination. Adaptation involves aligning with the changing market environment, while coordination ensures the complementarity of employees' efforts. Dessein and Santos (2006) explore how organizations coordinate to adapt to local environments, considering the breadth of tasks employees acquire.

I built the model based on Dessein and Santos (2006), assuming that employees are non-identical with different characteristics. Employees are categorized as specialists and generalists. Specialization of worker skills is defined by the intensity of task experience, assuming that specialists and generalists

[25] According to Figure A.4, the ratio of specialists who have experienced up to two areas tends to be flat relative to Market Beta in business investment areas owing to the high value of Infrastructure, whereas that of commodity trading has a slightly downward trend. This results in a relatively positive coefficient.

[26] The interaction term between the business investment dummy and Market Beta exhibit insignificant negative coefficients in Table A.3. However, the coefficients of Market Beta are significantly positive, indicating that as market uncertainty increases, divisions tend to have more generalists.

Table 5: Estimation Results on Other Career Specialization Indices

	(1) Only One Area	(2) Only One Area	(3) Up to Two Areas	(4) Up to Two Areas	(5) Ratio of Curr. Area	(6) Ratio of Curr. Area
Business Investment:						
Consumer Business (Reference)						
Infrastructure	-0.030		0.030		0.032	
	(0.053)		(0.083)		(0.047)	
Energy	0.023		0.006		0.042	
	(0.045)		(0.069)		(0.042)	
Agriculture	0.049		0.071		0.128***	
	(0.047)		(0.069)		(0.040)	
Commodity Trading:						
Machinery	0.070		0.142*		0.179***	
	(0.059)		(0.075)		(0.043)	
Chemicals	0.089*		0.227***		0.146***	
	(0.049)		(0.064)		(0.039)	
Metals	0.068		0.173***		0.219***	
	(0.050)		(0.066)		(0.038)	
Uncertainty:						
Business Investment * Market Beta		-0.118		0.026		-0.397***
		(0.171)		(0.217)		(0.122)
Business Investment		0.036		-0.221		0.291**
		(0.194)		(0.236)		(0.134)
Market Beta		-0.045		-0.109		0.176**
		(0.132)		(0.143)		(0.080)
Base Controls	✓	✓	✓	✓	✓	✓
+Female, Education and Marriage	✓	✓	✓	✓	✓	✓
+Managerial Position	✓	✓	✓	✓	✓	✓
Constant	-0.125	0.010	0.324	0.660***	0.764***	0.735***
	(0.177)	(0.227)	(0.203)	(0.243)	(0.130)	(0.145)
Adjusted R^2	0.012	0.016	0.130	0.131	0.085	0.079
# of obs	660	660	660	660	660	660

Robust standard errors are in parentheses.
Base controls include age, tenure, and the fiscal year of the most recent transfer.
*** p<0.01, ** p<0.5, * p<0.1.

have the same tenure. Specialists have an advantage in adaptation owing to their deep knowledge in a specific area but face challenges in coordination owing to their limited knowledge in other areas. In contrast, generalists excel in coordination owing to their broad knowledge but are less effective in adaptation. Using the framework, I examine the optimal organizational composition of specialists and generalists through a model incorporating parameters such as the importance of adaptation and coordination, uncertainty, training costs, and the probability of observing local market information.

The models yield several key implications. The optimal organizational composition shifts monotonically with the importance of coordination and market uncertainty. Specifically, as coordination or uncertainty becomes more important, the optimal composition shifts from one with many specialists to one with many generalists. Generalists, being adept at coordination, are preferable in organizations where coordination is critical for profitability. Regarding uncertainty, the relationship remains monotonic when coordination is sufficiently prioritized. In this scenario, increased uncertainty affects both adaptation and coordination costs. Generalists, who succeed in coordination with a high probability, can mitigate the coordination costs. Additionally, the importance of adaptation exhibits inversed monotonicity with optimal compositions because of the relative relationship with that of coordination.

These theoretical results lead to two empirical predictions: (1) organizations requiring higher coordination (relative to adaptation) will have more generalists, and (2) organizations facing higher market uncertainty will have more generalists when the importance of coordination is sufficiently important.

To test these predictions, I used employee-level data from a large Japanese trading company, which operates diverse industries, classified as commodity trading and business investment. I hypothesized that the importance of adaptation is more important in business investment areas, while coordination is more important in commodity trading, based on manager interviews.

The empirical hypotheses are as follows: (1) commodity trading divisions have more specialists than business investment divisions, and (2) the proportion of generalists in business investment divisions increases with the increase in Market Beta. I created five specialization measures using text data from employee assignment history records, spanning from their entry into the firm until 2023. These measures include career intensity estimated by unsupervised machine learning, the total number of business areas experienced, a specialist dummy variable indicating experience in only one business area, the other specialist dummy variable indicating experience in up to two business areas, and the career proportion of the current business area relative to the entire career in the trading company. Career intensity captures specialization in both business areas and more detailed department/section information in employee assignment records. Estimations of specialization yield results consistent with the model's predictions and empirical hypotheses.

This study has a limitation regarding its model, that is, it assumes that firms train workers through job rotation to maintain consistency with the empirical analysis. This is based on the idea that specialists accumulate human capital related to specific areas through on-the-job training, while generalists accumulate human capital through broader experiences by job rotation. I have room to analyze how optimal organizational compositions change when assuming firms where specialist employees accumulate human capital through off-the-job training, such as IT firms. This study also has a limitation regarding its cross-sectional analysis, that is, it cannot address unobservable confounding factors for specialization. Constructing a specialization index as a time-varying variable to make use of the panel data is key to improving this analysis. These points can be the subject of future research on optimal organization compositions of specialists and generalists.

In recent years, with the rapid evolution of the work environment, firms must adapt their human capital development strategies to emphasize specialization. Effective strategies are crucial for addressing the changing landscape. This study is the first to investigate the optimal composition of specialists and generalists in the context of coordination and adaptation, offering valuable insights for human resource management. The findings provide recommendations for aligning worker skill development with organizational characteristics, thereby enhancing a firm's competitiveness. This research also informs training and job assignment strategies to ensure optimal resource allocation within firms.

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A Appendix

A.1 Calculation Process of Equations (5), (6), and (7)

To derive the conditions under which each organizational composition is optimal, I begin by calculating pairwise relationships among S-S, S-G, and G-G.
$E[C|t_1 = t_2 = s] \leq E[C|t_1 = t_2 = g]$ is satisfied when:

$$
\begin{aligned}
&2p_\theta^s \frac{\phi\beta}{\phi+\beta}\sigma_\theta^2 + 2(1-p_\theta^s)\phi\sigma_\theta^2 + 2h_s \leq 2(1-p_\theta^g)\phi\sigma_\theta^2 + 2h_g \\
&\Rightarrow \frac{\beta}{\phi+\beta} \leq \frac{p_\theta^s - p_\theta^g}{p_\theta^s} + \frac{h_g - h_s}{p_\theta^s \phi \sigma_\theta^2}.
\end{aligned}
$$

$E[C|t_1 = t_2 = s] \leq E[C|t_1 = s, t_2 = g]$ is satisfied when:

$$
\begin{aligned}
&2p_\theta^s \frac{\phi\beta}{\phi+\beta}\sigma_\theta^2 + 2(1-p_\theta^s)\phi\sigma_\theta^2 + 2h_s \leq p_\theta^g \frac{\phi\beta}{\phi+\beta}\sigma_\theta^2 + (2-p_\theta^s-p_\theta^g)\phi\sigma_\theta^2 + h_s + h_g \\
&\Rightarrow \frac{\beta}{\phi+\beta} \leq \frac{p_\theta^s - p_\theta^g}{2p_\theta^s - p_\theta^g} + \frac{h_g - h_s}{(2p_\theta^s - p_\theta^g)\phi\sigma_\theta^2}.
\end{aligned}
$$

$E[C|t_1 = t_2 = g] \leq E[C|t_1 = s, t_2 = g]$ is satisfied when:

$$
\begin{aligned}
&2(1-p_\theta^g)\phi\sigma_\theta^2 + 2h_g \leq p_\theta^g \frac{\phi\beta}{\phi+\beta}\sigma_\theta^2 + (2-p_\theta^s-p_\theta^g)\phi\sigma_\theta^2 + h_s + h_g \\
&\Rightarrow \frac{p_\theta^s - p_\theta^g}{p_\theta^g} + \frac{h_g - h_s}{p_\theta^g \phi\sigma_\theta^2} \leq \frac{\beta}{\phi+\beta}.
\end{aligned}
$$

Now, I derive the conditions under which either S-S, S-G, or G-G is optimal by summarizing the above three pairwise relationships.
S-S is the least costly organizational composition when:

$$
\frac{\beta}{\phi+\beta} \leq \frac{p_\theta^s - p_\theta^g}{2p_\theta^s - p_\theta^g} + \frac{h_g - h_s}{(2p_\theta^s - p_\theta^g)\phi\sigma_\theta^2} \left(< \frac{p_\theta^s - p_\theta^g}{p_\theta^s} + \frac{h_g - h_s}{p_\theta^s \phi\sigma_\theta^2} \right).
$$

S-G is the least costly organizational composition when:

$$
\frac{p_\theta^s - p_\theta^g}{2p_\theta^s - p_\theta^g} + \frac{h_g - h_s}{(2p_\theta^s - p_\theta^g)\phi\sigma_\theta^2} \leq \frac{\beta}{\phi+\beta} \leq \frac{p_\theta^s - p_\theta^g}{p_\theta^g} + \frac{h_g - h_s}{p_\theta^g \phi\sigma_\theta^2}.
$$

G-G is the least costly organizational composition when:

$$
\left(\frac{p_\theta^s - p_\theta^g}{p_\theta^s} + \frac{h_g - h_s}{p_\theta^s \phi\sigma_\theta^2} < \right) \frac{p_\theta^s - p_\theta^g}{p_\theta^g} + \frac{h_g - h_s}{p_\theta^g \phi\sigma_\theta^2} \leq \frac{\beta}{\phi+\beta}.
$$

A.2 Propositions for Other Parameters

The propositions for h_{ti} and $p_\theta^{t_i}$ derived from comparative statics are as follows:

Proposition 3. *An organizational choice shifts from having more specialists to more generalists as the gap in training costs, $h_g - h_s$, increases from low to high.*
Proof is straightforward from Equations (5)–(7) and is thus omitted.

Proposition 4. *An organizational choice shifts from having more generalists to more specialists as the gap in observation probabilities of local information, $p^s_\theta - p^g_\theta$, increases from low to high, provided that $\frac{\beta}{\phi+\beta} \leq \frac{1}{2}$.*
Proof is provided in Appendix A.4.

Proposition 3 suggests that as the gap in training costs between specialists and generalists widens, specialists become increasingly preferred within the organization. As expected, the change in relative costs between specialists and generalists affects the optimal organizational composition. By definition, the gap $h_g - h_s$ exhibits monotonicity in terms of organizational composition without restrictions (see Definition 1 in Appendix A.4). However, thresholds such as $\frac{\beta}{\phi+\beta} > \frac{p^s_\theta - p^g_\theta}{2p^s_\theta - p^g_\theta}$ and $\frac{\beta}{\phi+\beta} \geq \frac{p^s_\theta - p^g_\theta}{p^g_\theta}$ must be met for the S-G and G-G compositions to become optimal, respectively. If the condition $\frac{\beta}{\phi+\beta} \geq \frac{p^s_\theta - p^g_\theta}{p^g_\theta}$ is not satisfied, the optimal composition shifts monotonically from S-S to S-G as $h_g - h_s$ decreases, but the G-G composition cannot be achieved even when $h_g - h_s$ is extremely low. Proposition 4 shows a similar tendency with respect to the gap in observation probabilities between specialists and generalists. When there is a skill gap in adaptation between specialists and generalists, the organization tends to favor specialists.

The importance of adaptation ϕ also exhibits monotonic relationships, under certain conditions. Figure A.1 illustrates the relationship between the costs of $\frac{\beta}{\beta+\phi}$, $SS(\phi, \sigma^2_\theta)$, and $GG(\phi, \sigma^2_\theta)$ with respect to the adaptation importance parameter, ϕ. When ϕ exceeds a certain threshold $\underline{\phi}$, an increase in the importance of adaptation shifts the optimal organizational composition from a generalist-dominant organization to a specialist-dominant organization. In cases where ϕ is sufficiently high, adapting to market demands and technological changes becomes critical to maximizing organizational profitability. Therefore, intensively assigning specialists who excel in their specific areas is more beneficial. The monotonicity in ϕ holds when the relative importance of coordination $\frac{\beta}{\phi+\beta}$ intersects with $GG(\phi, \sigma^2_\theta)$. Two conditions are required for this intersection. First, the threshold of $GG(\phi, \sigma^2_\theta)$, $\frac{p^s_\theta - p^g_\theta}{p^g_\theta}$ must be strictly less than 1, as the possible maximum value of $\frac{\beta}{\phi+\beta}$ is 1. This condition implies that the adaptation abilities of specialists and generalists are relatively close. Second, the gap in training costs $h_g - h_s$, which is part of $GG(\phi, \sigma^2_\theta)$ and $SS(\phi, \sigma^2_\theta)$ must also be small. This indicates that the training costs of specialists are sufficiently high and close to those of generalists.

The discussion leads me to the following proposition.

Proposition 5. *An organization's choice shifts from having generalists to having specialists as the importance of adaptation ϕ increases, provided that the following conditions are met:*

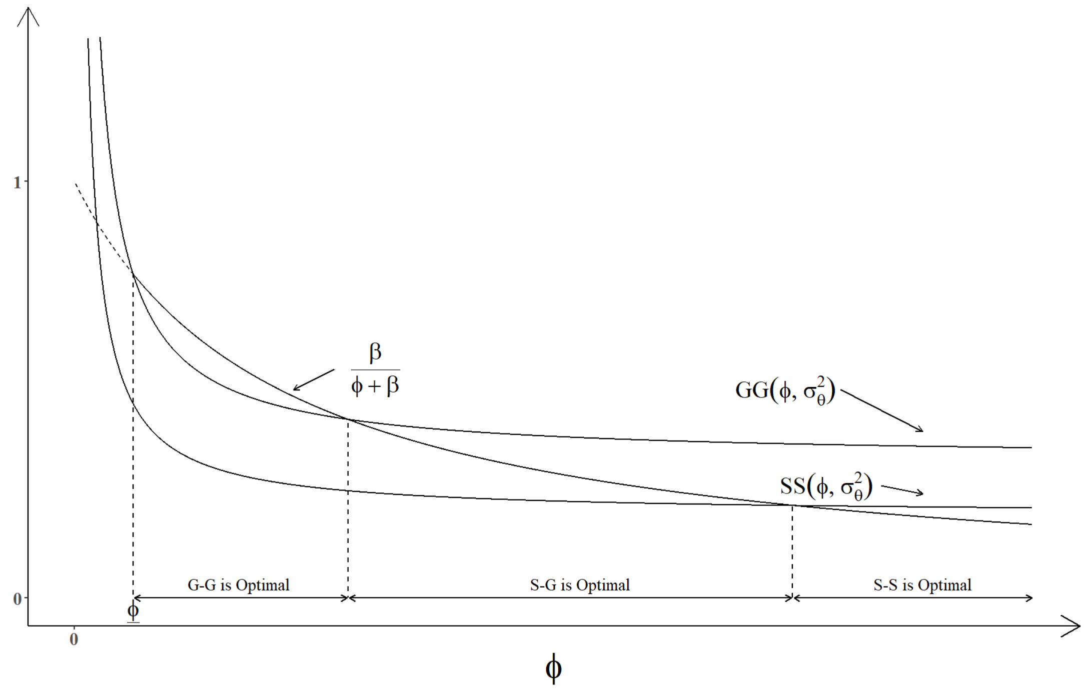
1. $\frac{p^s_\theta - p^g_\theta}{p^g_\theta}$ *(The threshold of $GG(\phi, \sigma^2_\theta)$)* < 1;
2. $h_g - h_s$ *is sufficiently low;*
3. $\phi \geq \underline{\phi}(h_g, h_s, p^g_\theta, p^s_\theta)$.

Proof in Appendix A.4.

The intuition behind these results is that organizations for which adaptation to the market is critical for profitability require a higher proportion of specialists, as they can effectively minimize adaptation losses compared to generalists. When adaptation skill gap $p^s_\theta - p^g_\theta$ or training cost gap $h_g - h_s$ is large, specialists are preferred, and organizations will favor specialists regardless of the value of ϕ. The coordination parameter, β, also plays a key role in interpreting the relationship. As β increases, the slope of $\frac{\beta}{\phi+\beta}$ becomes more gradual, expanding the range of ϕ where a G-G composition is optimal. Thus, even when ϕ is high, generalists remain valuable if β is also sufficiently large[27].

[27] When ϕ is sufficiently small, that is, $\phi \leq \underline{\phi}(h_g, h_s, p^g_\theta, p^s_\theta)$, organizations primarily engage in routine tasks that do not require workers to adapt local information. However, I exclude this scenario from the current model to maintain consistency with actual firm behavior and empirical analysis, as it is unrealistic to assume firms that completely disregard market adaptation.

Figure A.1: Relationship of Expected Costs in terms of Adaptation across Three Organizational Compositions



A.3 Complementarity between Specialists and Generalists

Suppose an organizational structure is S-G and the uncertainty of local information θ_1 is strictly lower than that of θ_2, that is, $\sigma^2_{\theta_1} < \sigma^2_{\theta_2}$. The expected total costs in the case that (1) a specialist handles task 2 and a generalist handles task 1, or (2) vice versa, are as follows.

$$E[C|t_1 = g, t_2 = s, \sigma^2_{\theta_1} < \sigma^2_{\theta_2}] = p^g_\theta \frac{\phi\beta}{\phi+\beta}\sigma^2_{\theta_1} + (1-p^s_\theta)\phi\sigma^2_{\theta_2} + (1-p^g_\theta)\phi\sigma^2_{\theta_1} + h_s + h_g \tag{A.1}$$

$$E[C|t_1 = s, t_2 = g, \sigma^2_{\theta_1} < \sigma^2_{\theta_2}] = p^g_\theta \frac{\phi\beta}{\phi+\beta}\sigma^2_{\theta_2} + (1-p^s_\theta)\phi\sigma^2_{\theta_1} + (1-p^g_\theta)\phi\sigma^2_{\theta_2} + h_s + h_g. \tag{A.2}$$

Then, comparing the value of Equations (A.1) and (A.2),

$$\begin{aligned} &E[C|t_1 = g, t_2 = s, \sigma^2_{\theta_1} < \sigma^2_{\theta_2}] - E[C|t_1 = s, t_2 = g, \sigma^2_{\theta_1} < \sigma^2_{\theta_2}] \\ &= p^g_\theta \frac{\phi\beta}{\phi+\beta}(\sigma^2_{\theta_1} - \sigma^2_{\theta_2}) - (p^s_\theta - p^g_\theta)(\sigma^2_{\theta_2} - \sigma^2_{\theta_1})\phi < 0. \end{aligned}$$

This demonstrates $E[C|t_1 = g, t_2 = s, \sigma^2_{\theta_1} < \sigma^2_{\theta_2}] < E[C|t_1 = s, t_2 = g, \sigma^2_{\theta_1} < \sigma^2_{\theta_2}]$. Therefore, assigning a specialist to task 2 and a generalist to task 1 is optimal if $\sigma^2_{\theta_1} < \sigma^2_{\theta_2}$ in the case of the structure S-G. This implies complementarity between specialists and generalists within an organization.

A.4 Proofs

Proof of Proposition 2. It suffices to demonstrate that the condition of monotonicity in the variance of local information σ^2_θ holds.

Definition 1. *Monotonicity: Suppose that the organization has these three types* $O \in \{1, 2, 3\}$ *(*$1 =$*S-S,* $2 =$*S-G,* $3 =$*G-G).* $E[C(\tau, O)]$ *is monotonic in terms of a parameter* $\tau \in \{\sigma_\theta, \beta, -h_g, h_s, -p^s_\theta, p^g_\theta\}$ *if* $\frac{\partial E[C(\tau,O)]}{\partial \tau}$ *is non-increasing in* O*. It is mathematically represented as*

$$\left.\frac{\partial E[C]}{\partial \tau}\right|_{O=3} \leq \left.\frac{\partial E[C]}{\partial \tau}\right|_{O=2} \leq \left.\frac{\partial E[C]}{\partial \tau}\right|_{O=1}.$$

The partial derivatives of the total expected cost $E[C|O]$ with respect to σ^2_θ in each organization type are as follows:

$$\begin{aligned}
\left.\frac{\partial E[C]}{\partial \sigma^2_\theta}\right|_{O=1} &= 2p^s_\theta \frac{\phi\beta}{\phi+\beta} + 2(1-p^s_\theta)\phi, \\
\left.\frac{\partial E[C]}{\partial \sigma^2_\theta}\right|_{O=2} &= (1-p^g_\theta)\phi + p^g_\theta \frac{\phi\beta}{\phi+\beta} + (1-p^g_\theta)\phi, \\
\left.\frac{\partial E[C]}{\partial \sigma^2_\theta}\right|_{O=3} &= 2(1-p^g_\theta)\phi.
\end{aligned}$$

$\left.\frac{\partial E[C]}{\partial \sigma^2_\theta}\right|_{O=3} \leq \left.\frac{\partial E[C]}{\partial \sigma^2_\theta}\right|_{O=1}$ holds when:

$$2(1-p^g_\theta)\phi \leq 2p^s_\theta \frac{\phi\beta}{\phi+\beta} + 2(1-p^s_\theta)\phi \Rightarrow \frac{\beta}{\phi+\beta} \geq \frac{p^s_\theta - p^g_\theta}{p^s_\theta}.$$

$\left.\frac{\partial E[C]}{\partial \sigma^2_\theta}\right|_{O=3} \leq \left.\frac{\partial E[C]}{\partial \sigma^2_\theta}\right|_{O=2}$ holds when:

$$2(1-p^g_\theta)\phi \leq (1-p^g_\theta)\phi + p^g_\theta \frac{\phi\beta}{\phi+\beta} + (1-p^g_\theta)\phi \Rightarrow \frac{\beta}{\phi+\beta} \geq \frac{p^s_\theta - p^g_\theta}{p^g_\theta}.$$

$\left.\frac{\partial E[C]}{\partial \sigma^2_\theta}\right|_{O=2} \leq \left.\frac{\partial E[C]}{\partial \sigma^2_\theta}\right|_{O=1}$ holds when:

$$(1-p^g_\theta)\phi + p^g_\theta \frac{\phi\beta}{\phi+\beta} + (1-p^g_\theta)\phi \leq 2p^s_\theta \frac{\phi\beta}{\phi+\beta} + 2(1-p^s_\theta)\phi \Rightarrow \frac{\beta}{\phi+\beta} \geq \frac{p^s_\theta - p^g_\theta}{2p^s_\theta - p^g_\theta}.$$

Therefore, monotonicity in σ^2_θ $\left.\frac{\partial E[C]}{\partial \sigma^2_\theta}\right|_{O=3} \leq \left.\frac{\partial E[C]}{\partial \sigma^2_\theta}\right|_{O=2} \leq \left.\frac{\partial E[C]}{\partial \sigma^2_\theta}\right|_{O=1}$ is satisfied when:

$$\frac{\beta}{\phi+\beta} \geq \frac{p^s_\theta - p^g_\theta}{p^g_\theta} \left(> \frac{p^s_\theta - p^g_\theta}{p^s_\theta} > \frac{p^s_\theta - p^g_\theta}{2p^s_\theta - p^g_\theta} \right).$$

(Q.E.D.)

Proof of Proposition 4. Similar to the proof of Proposition 2, it suffices to show that the condition of monotonicity in the probabilities of observing local information p^s_θ and p^g_θ holds.

The partial derivatives of the total expected cost $E[C|O]$ with respect to p^s_θ in each organization type are as follows:

$$\begin{aligned}
\left.\frac{\partial E[C]}{\partial p^s_\theta}\right|_{O=1} &= 2\frac{\phi\beta}{\phi+\beta}\sigma^2_\theta - 2\phi\sigma^2_\theta, \\
\left.\frac{\partial E[C]}{\partial p^s_\theta}\right|_{O=2} &= -\phi\sigma^2_\theta, \\
\left.\frac{\partial E[C]}{\partial p^s_\theta}\right|_{O=3} &= 0.
\end{aligned}$$

$\frac{\partial E[C]}{\partial p_\theta^s}\Big|_{O=1} \leq \frac{\partial E[C]}{\partial p_\theta^s}\Big|_{O=3}$ holds when:

$$2\frac{\phi\beta}{\phi+\beta}\sigma_\theta^2 - 2\phi\sigma_\theta^2 \leq 0 \Rightarrow \frac{\beta}{\beta+\phi} \leq 1.$$

$\frac{\partial E[C]}{\partial p_\theta^s}\Big|_{O=1} \leq \frac{\partial E[C]}{\partial p_\theta^s}\Big|_{O=2}$ holds when:

$$2\frac{\phi\beta}{\phi+\beta}\sigma_\theta^2 - 2\phi\sigma_\theta^2 \leq -\phi\sigma_\theta^2 \Rightarrow \frac{\beta}{\beta+\phi} \leq \frac{1}{2}.$$

$\frac{\partial E[C]}{\partial p^s}\Big|_{O=2} \leq \frac{\partial E[C]}{\partial p_\theta^s}\Big|_{O=3}$ holds when:

$$-\phi\sigma_\theta^2 \leq 0.$$

As both $\frac{\partial E[C]}{\partial p_\theta^s}\Big|_{O=1} \leq \frac{\partial E[C]}{\partial p_\theta^s}\Big|_{O=3}$ and $\frac{\partial E[C]}{\partial p_\theta^s}\Big|_{O=2} \leq \frac{\partial E[C]}{\partial p_\theta^s}\Big|_{O=3}$ always hold, monotonicity in p_θ^s which means $\frac{\partial E[C]}{\partial p_\theta^s}\Big|_{O=1} \leq \frac{\partial E[C]}{\partial p_\theta^s}\Big|_{O=2} \leq \frac{\partial E[C]}{\partial p_\theta^s}\Big|_{O=3}$ is satisfied when:

$$\frac{\beta}{\beta+\phi} \leq \frac{1}{2}.$$

In the case of p_θ^g, the partial derivatives of total expected costs $\frac{\partial E[C]}{\partial p_\theta^s}$ in each organization type are:

$$\begin{aligned}
\frac{\partial E[C]}{\partial p_\theta^s}\Big|_{O=1} &= 0, \\
\frac{\partial E[C]}{\partial p_\theta^s}\Big|_{O=2} &= \frac{\phi\beta}{\phi+\beta}\sigma_\theta^2 - \phi\sigma_\theta^2, \\
\frac{\partial E[C]}{\partial p_\theta^s}\Big|_{O=3} &= -2\phi\sigma_\theta^2.
\end{aligned}$$

$\frac{\partial E[C]}{\partial p_\theta^s}\Big|_{O=3} \leq \frac{\partial E[C]}{\partial p_\theta^s}\Big|_{O=1}$ holds when

$$-2\phi\sigma_\theta^2 \leq 0.$$

$\frac{\partial E[C]}{\partial p_\theta^s}\Big|_{O=3} \leq \frac{\partial E[C]}{\partial p_\theta^s}\Big|_{O=2}$ holds when

$$-2\phi\sigma_\theta^2 \leq \frac{\phi\beta}{\phi+\beta}\sigma_\theta^2 - \phi\sigma_\theta^2 \Rightarrow -1 \leq \frac{\beta}{\beta+\phi}.$$

$\frac{\partial E[C]}{\partial p_\theta^s}\Big|_{O=2} \leq \frac{\partial E[C]}{\partial p_\theta^s}\Big|_{O=1}$ holds when

$$\frac{\phi\beta}{\phi+\beta}\sigma_\theta^2 - \phi\sigma_\theta^2 \leq 0 \Rightarrow \frac{\beta}{\beta+\phi} \leq 1.$$

As above three inequalities always hold, the monotonicity $\frac{\partial E[C]}{\partial p_\theta^s}\Big|_{O=3} \leq \frac{\partial E[C]}{\partial p_\theta^s}\Big|_{O=2} \leq \frac{\partial E[C]}{\partial p_\theta^s}\Big|_{O=1}$ is always satisfied. Therefore, monotonicity in $p_\theta^s - p_\theta^g$ holds if $\frac{\beta}{\beta+\phi} \leq \frac{1}{2}$, which is shown in the case of p_θ^s. (Q.E.D.)

Proof of Proposition 5. It suffices to show that there exists positive ϕ satisfying $\frac{\beta}{\phi+\beta} \geq GG(\phi, \sigma_\theta^2)$. As $\frac{\beta}{\phi+\beta} < 1$, $GG(\phi, \sigma_\theta^2)$ and its threshold $\frac{p_\theta^s - p_\theta^g}{p_\theta^g}$ must be strictly less than 1.

$$
\begin{aligned}
\frac{\beta}{\phi+\beta} &\geq GG(\phi, \sigma_\theta^2) \\
\frac{\beta}{\phi+\beta} &\geq \frac{p_\theta^s - p_\theta^g}{p_\theta^g} + \frac{h_g - h_s}{p_\theta^g \phi \sigma_\theta^2} \\
\beta &\geq (\phi+\beta)\left(\frac{p_\theta^s - p_\theta^g}{p_\theta^g} + \frac{h_g - h_s}{p_\theta^g \phi \sigma_\theta^2}\right) \\
0 &\geq \frac{p_\theta^s - p_\theta^g}{p_\theta^g}\phi^2 + \left(\frac{p_\theta^s - 2p_\theta^g}{p_\theta^g}\beta + \frac{h_g - h_s}{p_\theta^g \sigma_\theta^2}\right)\phi + \frac{h_g - h_s}{p_\theta^g \sigma_\theta^2}\beta \\
0 &\geq (p_\theta^s - p_\theta^g)\,\phi^2 + \left((p_\theta^s - 2p_\theta^g)\beta + \frac{h_g - h_s}{\sigma_\theta^2}\right)\phi + \frac{h_g - h_s}{\sigma_\theta^2}\beta \\
\phi &\geq \frac{\beta(2p_\theta^g - p_\theta^s) - \frac{(h_g - h_s)}{\sigma_\theta^2} - \sqrt{\left(\beta(2p_\theta^g - p_\theta^s) - \frac{(h_g - h_s)}{\sigma_\theta^2}\right)^2 - 4(p_\theta^s - p_\theta^g)\frac{(h_g - h_s)\beta}{\sigma_\theta^2}}}{2(p_\theta^s - p_\theta^g)}
\end{aligned}
$$

The right-hand side can be denoted as $\underline{\phi}(h_g, h_s, p_\theta^s, p_\theta^g)$. The conditions that the equation has positive solutions are:

1. $\beta(2p_\theta^g - p_\theta^s) - \frac{(h_g - h_s)}{\sigma_\theta^2} > 0$,

2. $\left(\beta(2p_\theta^g - p_\theta^s) - \frac{(h_g - h_s)}{\sigma_\theta^2}\right)^2 - 4(p_\theta^s - p_\theta^g)\frac{(h_g - h_s)\beta}{\sigma_\theta^2} > 0$.

Given that $\frac{\beta}{\phi+\beta} < 1$, the above two conditions are satisfied when $h_g - h_s$ is sufficiently low.

In the case $\phi \geq \underline{\phi}(h_g, h_s, p_\theta^s, p_\theta^g)$, there exists the ϕ satisfying $\frac{\beta}{\phi+\beta} \leq GG(\phi, \sigma_\theta^2)$ and $\frac{\beta}{\phi+\beta} \leq SS(\phi, \sigma_\theta^2)$ because as ϕ increases, $\frac{\beta}{\phi+\beta}$ convergences to zero while $GG(\phi, \sigma_\theta^2)$ and $SS(\phi, \sigma_\theta^2)$ convergence to each threshold, $\frac{p_\theta^s - p_\theta^g}{p_\theta^g} > 0$ and $\frac{p_\theta^s - p_\theta^g}{2p_\theta^s - p_\theta^g} > 0$, respectively. As $SS(\phi, \sigma_\theta^2) < GG(\phi, \sigma_\theta^2)$, the optimal organization composition monotonically shifts from G-G to S-S as ϕ, where $\phi \geq \underline{\phi}(h_g, h_s, p_\theta^s, p_\theta^g)$ is satisfied, increases. (Q.E.D.)

A.5 Relaxing the Assumption of Coordination

Consider relaxing the assumption of perfect coordination, where a generalist does not always coordinate perfectly but succeeds with a probability higher than that of a specialist. All other settings, except for the coordination success probability, remain as in Section 5. Let $q_c^{t_i}$ represent the probability of coordination success. If worker i coordinates successfully with probability $q_c^{t_i}$, perfect coordination is achieved, meaning $a_{ij} = a_{jj}$. Conversely, if coordination fails, occurring with probability $1 - q_c^{t_i}$, worker i's complementary action defaults to the expected value of the counterpart's primary action, $a_{ij} = E[a_{jj}] = E[\theta_i] = 0$. As a generalist is superior to a specialist in coordination, it follows that $q_c^g > q_c^s$.

Table A.1 summarizes the actions and costs for worker 1, considering coordination success probabilities. The total organizational costs for each composition are computed by summing the individual workers' costs:

Table A.1: Summary of Actions and Costs with Coordination Probability

Worker 2's Coord. prob.:	1's pri. act. a^*_{11}	2's comp. act. a^*_{21}	c_1	
$1-q_c^{t_2}$	$\begin{cases} \frac{\phi}{\phi+\beta}\theta_1 & \text{(with } p_\theta^{t_1}) \\ 0 & \text{(with } 1-p_\theta^{t_1}) \end{cases}$	0	$(1-q_c^{t_2})\left\{p_\theta^{t_1}\frac{\phi\beta}{\phi+\beta}\sigma_\theta^2+(1-p_\theta^{t_1})\phi\sigma_\theta^2\right\}$	(A)
$q_c^{t_2}$	$\begin{cases} \theta_1 & \text{(with } p_\theta^{t_1}) \\ 0 & \text{(with } 1-p_\theta^{t_1}) \end{cases}$	a_{11}	$q_c^{t_2}\left\{(1-p_\theta^{t_1})\phi\sigma_\theta^2\right\}$	(B)

$$E[C|t_1=s,t_2=s]=2p_\theta^s(1-q_c^s)\frac{\phi\beta}{\phi+\beta}\sigma_\theta^2+2(1-p_\theta^s)\phi\sigma_\theta^2+2h_s \tag{A.3}$$

$$E[C|t_1=s,t_2=g]=\left\{(1-q_c^s)p_\theta^g+(1-q_c^g)p_\theta^s\right\}\frac{\phi\beta}{\phi+\beta}\sigma_\theta^2 + (2-p_\theta^s-p_\theta^g)\phi\sigma_\theta^2+h_s+h_g \tag{A.4}$$

$$E[C|t_1=g,t_2=g]=2p_\theta^g(1-q_c^g)\frac{\phi\beta}{\phi+\beta}\sigma_\theta^2+2(1-p_\theta^g)\phi\sigma_\theta^2+2h_g \tag{A.5}$$

By comparing the costs determined by Equations (A.3)–(A.5), I derive the conditions for the lowest-cost organizational composition based on the relative importance of coordination, $\frac{\beta}{\phi+\beta}$.
S-S is the least costly organizational composition when:

$$\frac{\beta}{\phi+\beta}\leq\frac{1}{p_\theta^s(1-2q_c^s+q_c^g)-p_\theta^g(1-q_c^s)}\left(p_\theta^s-p_\theta^g+\frac{h_g-h_s}{\phi\sigma_\theta^2}\right) \left(<\frac{1}{p_\theta^s(1-q_c^s)-p_\theta^g(1-q_c^g)}\left(p_\theta^s-p_\theta^g+\frac{h_g-h_s}{\phi\sigma_\theta^2}\right)\right) \tag{A.6}$$

S-G is the least costly organizational composition when:

$$p_\theta^s(1-2q_c^s+q_c^g)-p_\theta^g(1-q_c^s)\left(p_\theta^s-p_\theta^g+\frac{h_g-h_s}{\phi\sigma_\theta^2}\right)\leq\frac{\beta}{\phi+\beta} \leq\frac{1}{p_\theta^s(1-q_c^g)-p_\theta^g(1-2q_c^g+q_c^s)}\left(p_\theta^s-p_\theta^g+\frac{h_g-h_s}{\phi\sigma_\theta^2}\right) \tag{A.7}$$

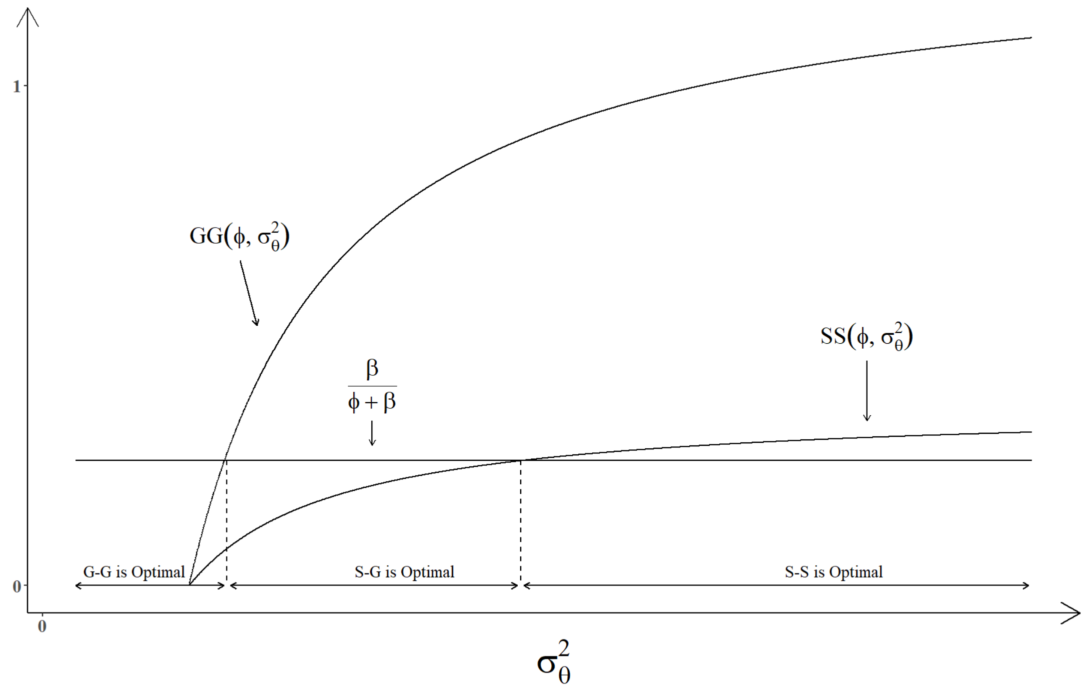
G-G is the least costly organizational composition when:

$$\left(\frac{1}{p_\theta^s(1-q_c^s)-p_\theta^g(1-q_c^g)}\left(p_\theta^s-p_\theta^g+\frac{h_g-h_s}{\phi\sigma_\theta^2}\right)<\right) \frac{1}{p_\theta^s(1-q_c^g)-p_\theta^g(1-2q_c^g+q_c^s)}\left(p_\theta^s-p_\theta^g+\frac{h_g-h_s}{\phi\sigma_\theta^2}\right)\leq\frac{\beta}{\phi+\beta} \tag{A.8}$$

Equations (A.6)-(A.8) have the same tendency as Equations (5)-(7) in Section 5 in terms of main parameters of the importance of coordination β, the importance of adaptation ϕ, and market uncertainty σ_θ^2.

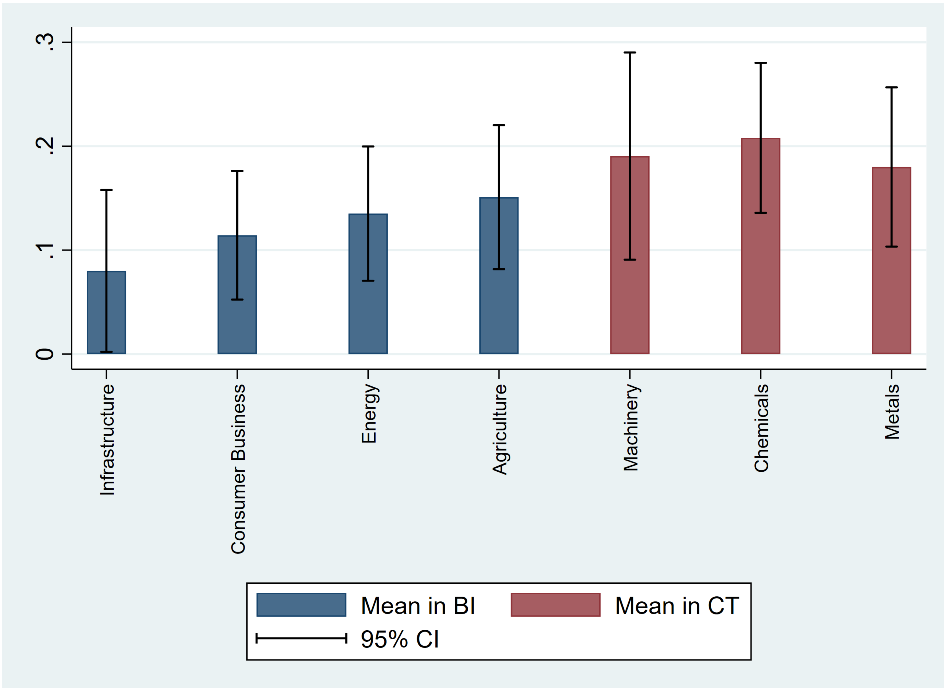
A.6 The Case when the Training Cost of Specialists is Higher than that of Generalists

Figure A.2: Relationship of Expected Costs in terms of Uncertainty across Three Organizational Compositions when $h_g < h_s$



A.7 Descriptive Results of Specialization for Other Indices

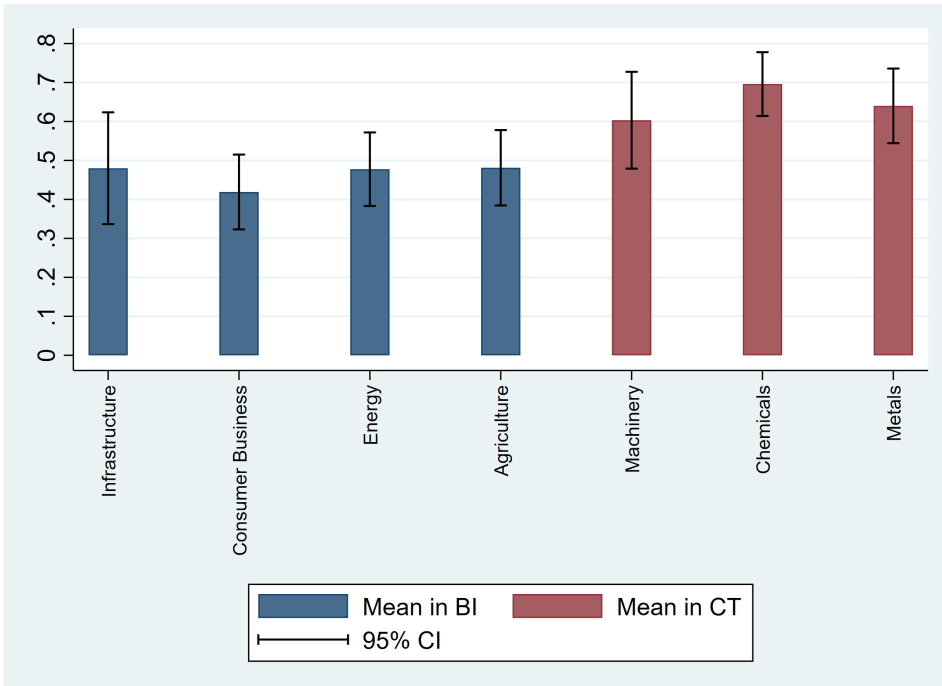
Figure A.3: Comparing Specialization among Business Areas (Experience in Only One Business Area)



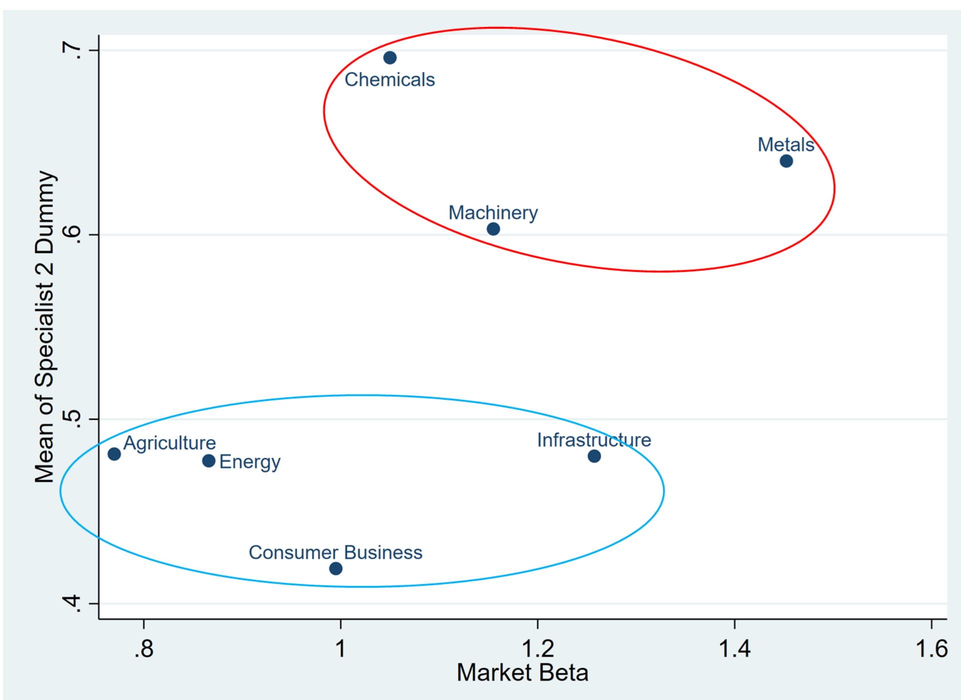
Panel A: Averages

Panel B: A Scatter plot between specialization and market uncertainty

Figure A.4: Comparing Specialization among Business Areas (Experience in Up to Two Business Areas)

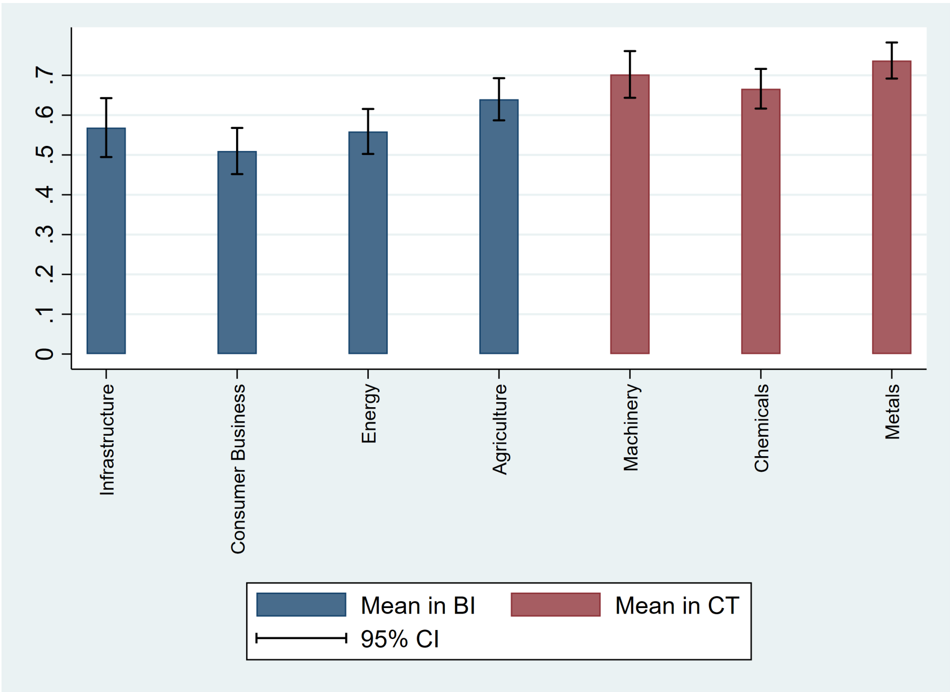


Panel A: Averages



Panel B: A Scatter plot between specialization and market uncertainty

Figure A.5: Comparing Specialization among Business Areas (Proportion of Experience in the Current Business Area)

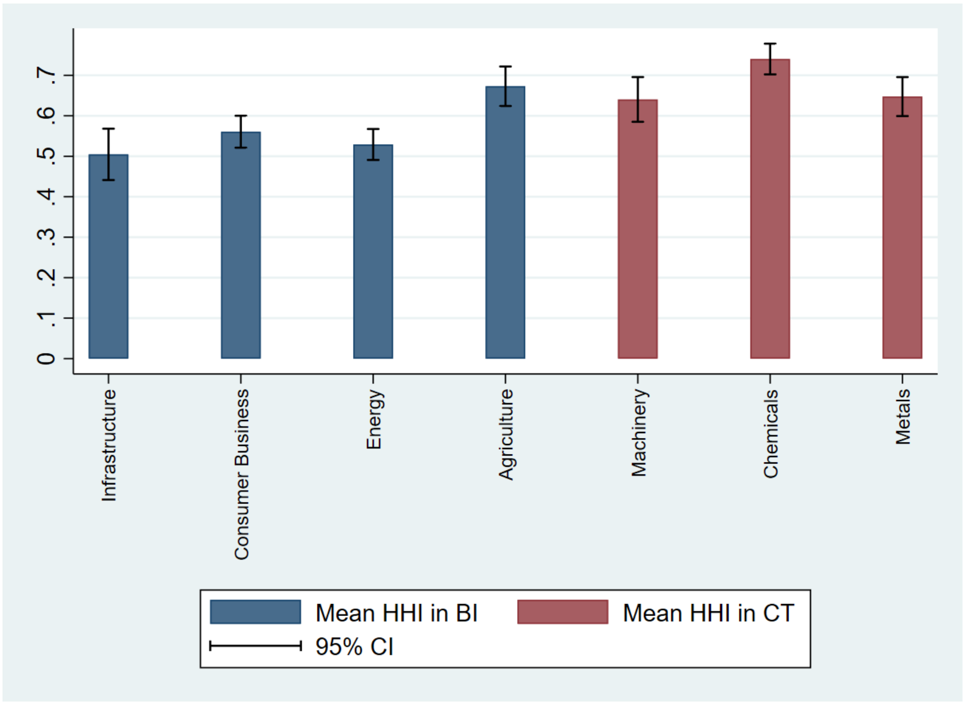


Panel A: Averages

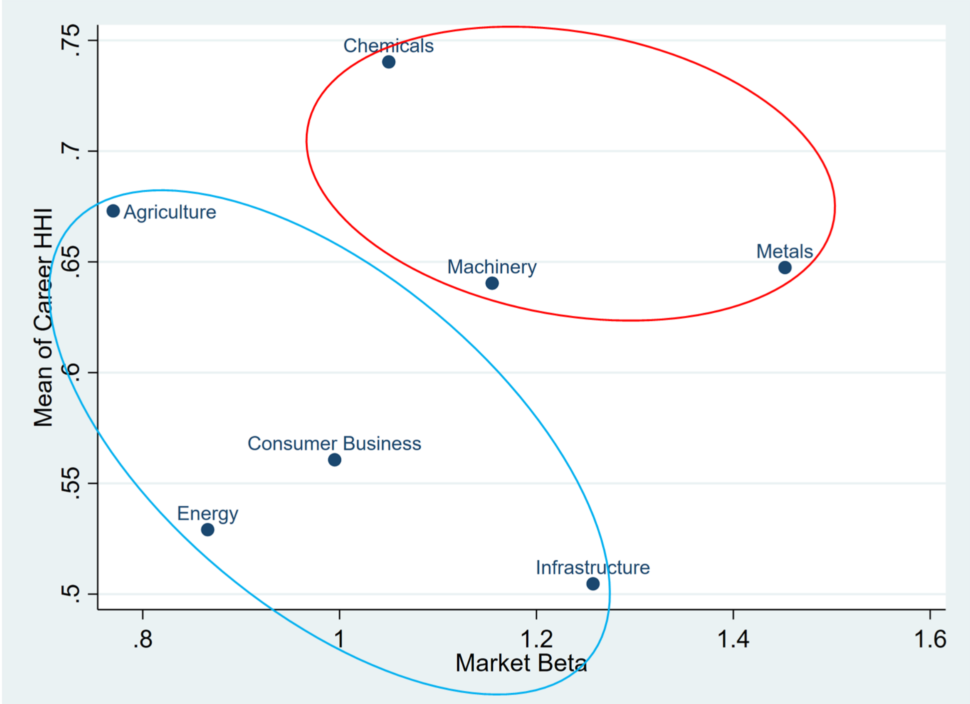
Panel B: A Scatter plot between specialization and market uncertainty

A.8 Results of Specialization for the Different Number of Topics in LDA

Figure A.6: Comparing Specialization in the Case of 15 Topics

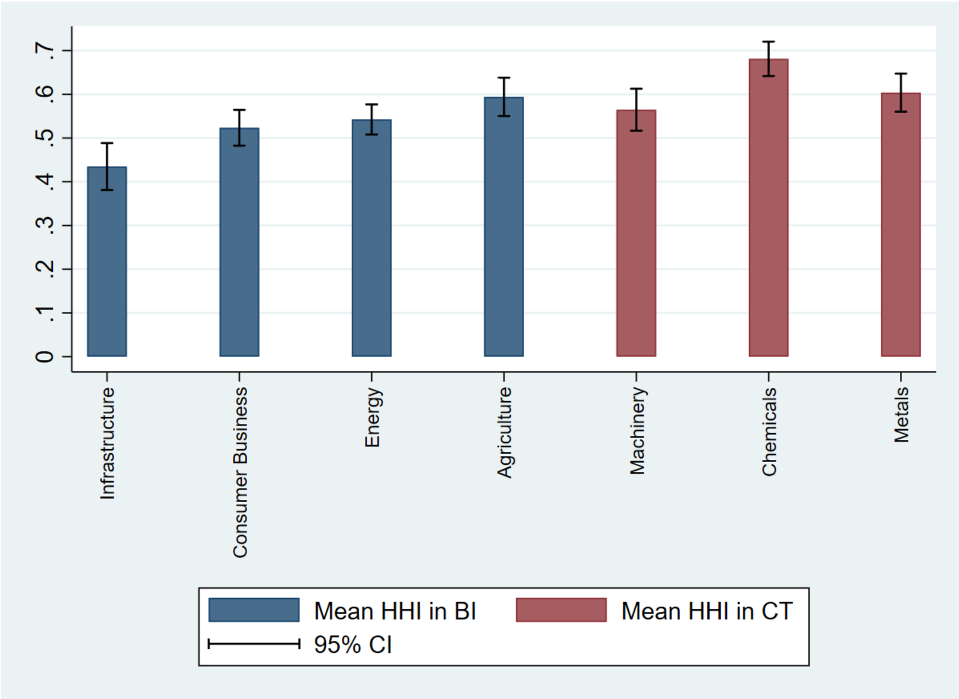


Panel A: Averages

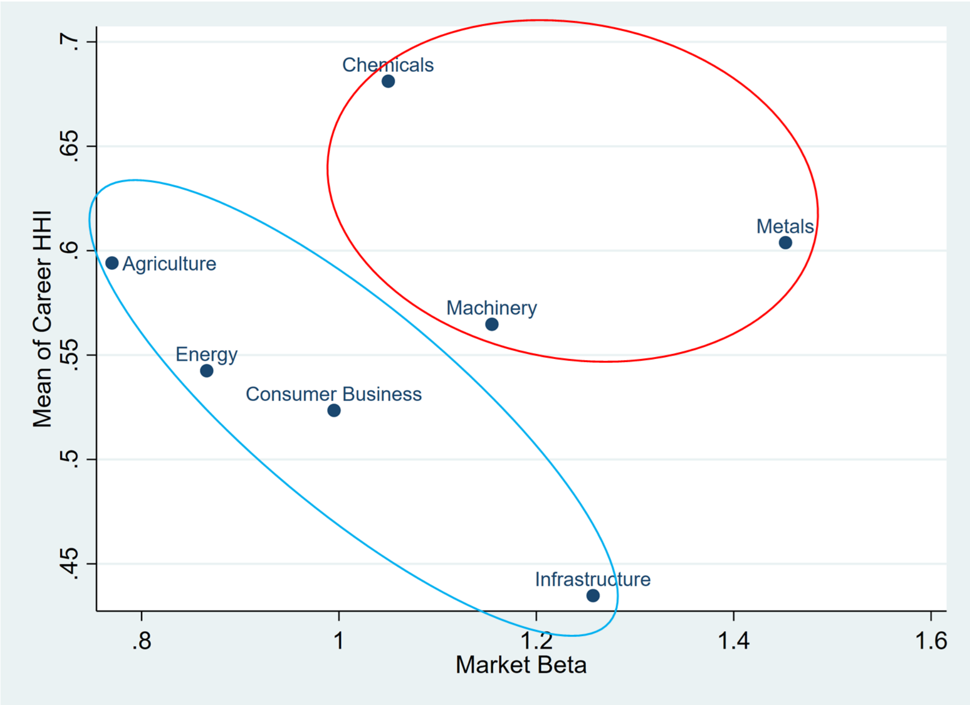


Panel B: A Scatter plot between specialization and market uncertainty

Figure A.7: Comparing Specialization in the Case of 25 Topics



Panel A: Average



Panel B: A Scatter plot between specialization and market uncertainty

Table A.2: Estimation Results of Career HHI with 15 and 25 Topics and Business Areas

	(1) 15 Topics	(2) 15 Topics	(3) 15 Topics	(4) 25 Topics	(5) 25 Topics	(6) 25 Topics
Business Investment:						
Consumer Business (Reference)						
Infrastructure	-0.042	-0.038	-0.038	-0.080**	-0.078**	-0.077**
	(0.039)	(0.040)	(0.040)	(0.036)	(0.036)	(0.036)
Energy	-0.033	-0.032	-0.032	0.020	0.021	0.021
	(0.028)	(0.029)	(0.029)	(0.028)	(0.028)	(0.028)
Agriculture	0.120***	0.121***	0.121***	0.079**	0.080**	0.080**
	(0.033)	(0.032)	(0.032)	(0.031)	(0.031)	(0.031)
Commodity Trading:						
Machinery	0.076**	0.078**	0.078**	0.034	0.036	0.036
	(0.035)	(0.035)	(0.035)	(0.032)	(0.032)	(0.032)
Chemicals	0.178***	0.178***	0.179***	0.153***	0.153***	0.154***
	(0.028)	(0.028)	(0.028)	(0.029)	(0.029)	(0.029)
Metals	0.087***	0.085***	0.085***	0.083***	0.082***	0.081***
	(0.032)	(0.032)	(0.032)	(0.031)	(0.031)	(0.031)
Base Controls	✓	✓	✓	✓	✓	✓
+Female, Education and Marriage		✓	✓		✓	✓
+Managerial Position			✓			✓
Constant	0.384***	0.357***	0.394***	0.346***	0.327***	0.359***
	(0.081)	(0.086)	(0.097)	(0.077)	(0.083)	(0.096)
Adjusted R^2	0.104	0.103	0.102	0.092	0.090	0.089
# of obs	660	660	660	660	660	660

Robust standard errors are in parentheses.
Base controls include age, tenure, and the fiscal year of the most recent transfer.
*** p<0.01, ** p<0.5, * p<0.1.

Table A.3: Estimation Results of Career HHI with 15 and 25 Topics and Uncertainty

	(1) 15 Topics	(2) 15 Topics	(3) 15 Topics	(4) 25 Topics	(5) 25 Topics	(6) 25 Topics
Business Investment * Market Beta	-0.082	-0.075	-0.071	-0.168*	-0.164	-0.160
	(0.113)	(0.113)	(0.113)	(0.102)	(0.103)	(0.103)
Business Investment	-0.089	-0.095	-0.100	0.031	0.027	0.023
	(0.122)	(0.123)	(0.123)	(0.112)	(0.113)	(0.114)
Market Beta	-0.197**	-0.201***	-0.204***	-0.138*	-0.141*	-0.143*
	(0.077)	(0.078)	(0.078)	(0.073)	(0.073)	(0.074)
Base Controls	✓	✓	✓	✓	✓	✓
+Female, Education and Marriage		✓	✓		✓	✓
+Managerial Position			✓			✓
Constant	0.747***	0.726***	0.764***	0.633***	0.615***	0.648***
	(0.112)	(0.114)	(0.125)	(0.105)	(0.107)	(0.120)
Adjusted R^2	0.076	0.075	0.074	0.079	0.078	0.077
# of obs	660	660	660	660	660	660

Robust standard errors are in parentheses.
Base controls include age, tenure, and the fiscal year of the most recent transfer.
*** p<0.01, ** p<0.5, * p<0.1.