ESSAYS ON LEARNING-BY-DOING AFTER INFORMATION SYSTEMS IMPLEMENTATION IN DEVELOPING COUNTRIES: THE CASE OF COSTA RICA

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ESSAYS ON LEARNING-BY-DOING AFTER INFORMATION SYSTEMS IMPLEMENTATION IN DEVELOPING COUNTRIES: THE CASE OF COSTA RICA

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SUMMARY

Developing countries are increasing their adoption of information systems at the country level now. One important aspect distinguishing the implementation of information systems in developing countries from that in developed countries is that developing countries usually lack the resources and capability for training and support, and the workers need to learn to use the system from their own experience. Thus, a better understanding of the workers' learning-by-doing after the implementation of an information system in developing countries may have important theoretical and practical implications, but empirical evidence on this issue remains limited. This dissertation seeks to fill in the gap by investigating workers' learning-by-doing after the implementation of an information system at two levels. First, it studies how an individual customs agent' experience preparing and submitting customs documents influences her performance in document preparation and submission tasks. Second, it also examines how an agent-inspector dyad's experience working together affects the performance of customs inspection tasks completed through the cooperation of the dyad.

The first chapter provides an overview of the dissertation. The second chapter examines how the relatedness of workers' prior experience affects their learning-by-doing and operational performance in service work. Prior research has viewed relatedness along a single dimension. However, tasks and the underlying knowledge required for task performance can vary along multiple attributes. This chapter extends prior conceptualizations of relatedness by defining it as a multi-dimensional construct and also accounting for the level of task relatedness between different categories in each task

dimension. It separates the level of workers' experience from the relatedness of their experience, and then link the two constructs to workers' task performance, including their efficiency and quality. Analyzing data on the processing of 998,258 import customs declarations in Costa Rica from 2006-2010, the second chapter finds that customs agents, the major workers processing the customs declarations, learn from their experience to improve their time to complete the task but not their quality of completion. Moreover, it finds that the relatedness of customs agents' experience to their current task is positively related to the quality of task completion but has a U-shape relationship with completion time, such that the completion time first decreases with and then increases with an increase in customs agents' experience relatedness. The chapter also finds that the impact of customs agents' experience relatedness is enhanced when the agents have more experience. Overall, the results highlight the role of experience relatedness in workers' performance in learning-by-doing service work, and help to identify ways for managers to improve different operational performance measures.

Many service tasks are completed by dyads rather than by an individual worker. In this setting, the individuals in the dyad not only need to acquire knowledge about the task, but also have to learn to work with each other. Thus, individuals' experience working together may have significant performance implications for dyads. However, this effect remains largely unexamined, especially when there are conflicts within the dyad. In the third chapter, it theorizes how a dyad's experience working together influences the dyad's task performance, and label it as a learning-by-working-together effect. The chapter further proposes that the impact of dyad experience can vary across tasks with different levels of complexity, goal conflict, and combinations of the two. It examines learning-by-working-together in a setting where there is goal conflict, but the dyad must work together to complete the task: customs inspections. Based on a field study on data of 323,520 customs inspections in Costa Rica, the third chapter shows that the number of prior interactions between a customs agent and a customs inspector is positively associated with the agent-inspector dyad's efficiency in customs inspection. In addition, it demonstrates that the impact of an agent-inspector dyad's experience working together is greater for high-complexity tasks than for low-complexity tasks, and weaker for high-conflict tasks than for low-conflict tasks. It also shows that due to a joint effect of task complexity and task-level goal conflict, dyad experience exhibits the largest impact on the performance of high-complexity, high-conflict tasks. The chapter discusses the implications of our results for the study of learning curves and for the practice.

CHAPTER 1

INTRODUCTION

Developing countries are increasing their adoption of information systems at the country level now. For example, customs automation systems have been implemented by many developing countries, such as Costa Rica and Panama. Compared with developed countries, implementation of information systems in developing countries can have interesting impact on the stakeholders, because there are huge differences between developing countries and developed countries in many aspects, such as the availability of resources for training and support (Ndou, 2004). Nonetheless, understanding of nation-wide information systems implementation and usage in the developing countries is still limited (Walsham et al., 2007).

One important aspect distinguishing the implementation of information systems in developing countries from that in developed countries is that developing countries usually lack the resources and capability for training and support (Ndou, 2004). According to the IS business value literature, due to the complexity and novelty of information technology and information systems, active learning of the system may be required for firms and individual users to capture value from them (Brynjolfsson, 1993). When there is little training provided to the workers using the information systems, the workers need to learn to use the system from their own experience. Further, information systems can also bring significant changes to the task, and the workers have to adapt to the new policies and procedures via their experience performing the tasks in the system. Such learning effect is referred as "learning-by-doing" in the literature (Arrow, 1962). Thus, a better understanding of the workers' learning-by-doing after the implementation of an information system in developing countries may have important theoretical and practical implications.

In this thesis, we seek to investigate workers' learning-by-doing after the implementation of an information system in one specific developing country in the Central America region: Costa Rica. In particular, we choose to study one specific information system: the customs automation system, which was implemented in 2005. We have several reasons for choosing this setting. First, as a developing country, Costa Rica has been growing rapidly and it aimed to become the technology leader in the Central America region. To achieve this goal, the country proposed a huge digital government plan at 2000 and updated it every five years. In practice, Costa Rica has already implemented many nation-wide informations systems, such as customs automation system, government procurement system, e-banking and tax payment, digital health records, criminal e-file, etc. Those systems provide many opportunities for understanding workers' learning-by-doing after information systems implementation.

In addition, as an important hub in the Central America region, Costa Rica relies heavily on its international trade, and customs processing becomes an important activity to ensure and facilitate the successful completion of the trade. In Costa Rica, customs processing is knowledge-intensive and involves significant learning-by-doing by the workers who perform the tasks, including the customs agents and the customs inspectors. Customs agents are third-party individuals employed by importers and exporters to clear the goods through the customs. Their major services include the preparation and submission of customs declarations[1] to the customs for validation and (possibly) inspection. On the other hand, customs inspectors are government employees who conduct inspections of customs documents and physical goods. Their major responsibility is to figure out problems such as errors in tariff codes, and to ensure the collection of customs duties. Both customs agents and customs inspectors are required to hold relevant educational degrees to become eligible to work. In addition, the knowledge required for processing customs declarations is often not captured in textbooks or manuals, and the agents and the inspectors have to rely on their experience with the task. As a result, the context of customs processing offers an excellent opportunity to study the workers' learning-by-doing and its implications on task performance.

Besides, the implementation of the customs automation system in our setting radically changed the customs procedure and the customs policies. In addition, our interviews suggest there was little training and support offered to the workers. For example, the government call center to address problems with the system usually has only one person to answer the calls. Thus, the workers (i.e., the agents and inspectors) may only rely on their own experience to learn to use the system and perform the tasks in the system, and the workers' learning-by-doing may be quite salient under our setting. Further, in certain tasks such as customs inspections, the successful completion of the task requires the cooperation of a customs agent and a customs inspector, and the learning may be bilateral. The agent and the inspector may not only need to learn to perform the task by themselves,

[1] Customs declarations are statements to declare that the entry or exit of goods is legal and conforms to the regulations. It is required for all international transactions in Costa Rica, including both imports and exports.

but also need to learn to work with each other. This could also have interesting implications on the workers' task performance.

This dissertation seeks to answer the following question: how does workers' learning-by-doing affect their performance in customs processing tasks? We particularly examine the workers' learning-by-doing at two levels: (i) how an individual customs agent' experience preparing and submitting customs documents influences her performance in document preparation and submission tasks, and (ii) how an agent-inspector dyad's experience working together affects the performance of customs inspection tasks completed through the cooperation of the dyad.

More specifically, in chapter 2, we investigate how the relatedness of workers' experience to the current task affects their learning-by-doing and task performance. Prior research has viewed relatedness along a single dimension (e.g., Boh, Slaughter, and Espinosa, 2007; Clark, Huckman, and Staats, 2012; KC and Staats, 2012; Staats and Gino, 2012). However, tasks and the underlying knowledge required for task performance can vary along multiple attributes. We extend prior conceptualizations of relatedness by defining it as a multi-dimensional construct and also accounting for the level of task relatedness between different categories in each task dimension. We separate the level of workers' experience from the relatedness of their experience, and then link the two constructs to workers' task performance, including their efficiency and quality. We argue that while the level of workers' prior experience is positively associated with their performance, the relatedness of workers' experience may exhibit a U-shape relationship with their performance, because experience relatedness can affect workers' skills and motivation in different ways (Csikszentmihalyi, 1997; KC and Staats, 2012). Further, the impact of workers' experience relatedness also varies across different levels of their experience.

We test our hypotheses using data on the processing of 998,258 import customs declarations in Costa Rica from 2006 to 2010. We use the the traditional learning curve model with agent fixed effects to investigate the impact of customs agents' levels of experience and experience relatedness on their performance, including their completion time in processing a customs declaration using a customs automation system and their quality of declaration processing. We adopt an innovative approach to construct one of our key independent variable: the relatedness of workers' prior experience to the current task. We first identify four dimensions to characterize the task. According to the type of variables representing those task dimensions, we then create measures to compute the relatedness between the workers' prior experience and their current task in each task dimension. After that, we calculate the Euclidean distance from the workers' experience to the current task by setting the dimension-specific relatedness values of the current task to 1. Finally, we convert the Euclidean distance value to a Relatedess Index ranging from zero to one. In this way, we incorporate all task dimensions in constructing our Relatedness Index.

Our results shows that customs agents learn from their experience to improve their time to complete the task but not their quality of completion. Moreover, we find that the relatedness of customs agents' experience to their current task is positively related to the quality of task completion but has a U-shape relationship with completion time, such that the completion time first decreases with and then increases with an increase in customs agents' experience relatedness. We also observe that the impact of customs agents' experience relatedness is enhanced when the agents have more experience. These results are generally consistent under a variety of robustness checks, including estimations with alternative specifications of independent variables and with autocorrelated error structures.

While individual workers' learning-by-doing could be beneficial for their individual task performance, in many settings, tasks are not completed by a single worker but by a dyad, such as a worker and her client. Under such setting, the dyad needs to cooperate to produce the task output (Larsson and Bowen, 1989). This co-production of service may imply a bilateral learning in the dyad. Both individuals in the dyad have to learn to perform the task, and they also need to learn to work with each other. In chapter 3, we specifically examine the latter learning effect by testing the relationship between a dyad's experience working together and its task performance. We label this potential effect as an effect of *learning-by-working-together*. We argue that under the dyad setting where there are extensive conflicts between the individuals in the dyad, repeated interactions with each other can help the dyad to develop a mutual understanding with each other, achieve better information sharing, and establish a relationship with trust (Boone et al., 2008; Clark, Huckman, and Staats, 2012; Elfenbein and Zenger, 2013; Jehn and Shah, 1997; McEvily, Perrone, and Zaheer, 2003). The dyad can benefit from those factors in resolving the conflicts and improving their task performance. Further, we argue that the effect of a dyad's experience working together will be higher when the task is more complex, or the task involves a lower level of goal conflict, or the task is more complex and involves a higher level of goal conflict.

We evaluate our research hypotheses based on the data of 323,520 customs inspections in Costa Rica between 2005 and 2011. Utilizing the traditional learning curve model with dyad fixed effects, we show that the doubling of the number of prior interactions between a customs agent and a customs inspector is associated with a 5.8% increase in the agent-inspector dyad's efficiency in customs inspection. In addition, we demonstrate that the impact of an agent-inspector dyad's experience working together is greater for high-complexity tasks than for low-complexity tasks, such that the doubling of dyad experience is associated with a 6.45% improvement in dyad performance when task complexity is one standard deviation above the mean, compared to a 5.2% increase when task complexity is one standard deviation below the mean. We also find that the impact of dyad experience is weaker for high-conflict tasks than for low-conflict tasks. The doubling of an agent-inspector dyad's experience working together is associated with a 5.96% increase in their inspection time when the task-level goal conflict is one standard deviation above the mean and a 5.69% increase when the task-level goal conflict is one standard deviation below the mean. Further, we also show that due to a joint effect of task complexity and task-level goal conflict, dyad experience exhibits the largest impact on the performance of high-complexity, high-conflict tasks. Our findings are robust to alternative operationalizations of key independent variables and a subsample analysis.

CHAPTER 2

RELATEDNESS OF EXPERIENCE, LEARNING, AND PERFORMANCE IN SERVICE WORK: A STUDY OF CUSTOMS PROCESSING IN COSTA RICA

2.1 INTRODUCTION

As a widely-used concept in economic theories, learning-by-doing has attracted tremendous attention from scholars and practitioners. Learning-by-doing refers to the capability of workers to improve their task performance through their experience on the tasks (Arrow 1962). Prior literature has considered learning-by-doing as one of the major mechanisms driving the idea of "specialization" for individuals and organizations to improve operational performance (Argote, 1999; Huckman and Zinner, 2008; KC and Terwiesch, 2011; Taylor, 1911; Tsikriktsis, 2007). Past studies have also documented the benefits of such learning-by-doing at both the individual level and the organizational level (e.g., Yelle, 1979; Dutton and Thomas, 1984).

Although many scholars have shown the evidence of workers' learning-by-doing, most studies have focused on manufacturing work. Evidence of learning exists in industries such as electronics, machine tools, paper making, aircraft, steel, apparel, and automobiles (see Dutton and Thomas, 1984 and Argote, 1999 for a review of learning curve studies in manufacturing industries). On the other hand, it has been more difficult to detect the existence of learning-by-doing in service operations, especially in knowledge and service work (Boh, Slaughter, and Espinosa, 2007). This is because such work is usually less repetitive and codified, so the application of prior knowledge gained from experience to the current task is more difficult. Several studies have shown that workers still can learn from their experience to improve their performance in diverse service industries such as mail delivery, hospital work, software engineering, or architectural engineering, but with much lower learning rates than in manufacturing (Boh et al., 2007; Boone, Ganeshan, and Hicks, 2008; Pisano, Bohmer, and Edmondson, 2001; Reagans, Argote, and Brooks, 2005; Wiersma, 2007). Overall, there is still a strong need to understand how workers improve their operational performance as they obtain more experience.

In this study, we attempt to enrich the understanding of workers' learning-by-doing and performance in a particular service setting: customs processing in Costa Rica. Customs processing has become an activity that is increasing in importance, as the level of global trade has increased dramatically over the last decade. According to WTO (2012a), in 2011, the total value of merchandise exports from its members reached US$ 16.7 trillion, and the total value of commercial service exports is estimated at US$ 4.17 trillion. Those numbers represent an annual increase of 10% since 2005. As a result, it is critical for customs work to be performed correctly and efficiently. We further select Costa Rica as our research setting, because the country is an important hub in the Central America Region. It has land connections with North and South America, sea connections to East Asia, Australia, and European Union, and air connections to the majority of the world. In 2011, Costa Rica's import and export trade reached US$ 16.22 billion and 10.41 billion, respectively, which both ranked 2nd after Panama in the region (WTO, 2012b). Hence, customs processing is important for the economy of Costa Rica, and a better understanding of customs work in the country will have strong practical implications.

In Costa Rica, customs processing is knowledge-intensive and involves significant learning-by-doing by customs agents who perform the work. Customs agents are third-party individuals employed by importers and exporters to clear the goods through the customs. Their major services include the preparation and submission of customs declarations to the customs for validation and (possibly) inspection. Customs agents are required to hold relevant educational degrees to become eligible to work. In addition, the knowledge required for processing customs declarations is often not captured in textbooks or manuals, and the agents have to rely on their experience with the task. As a result, customs processing offers an excellent opportunity to study learning-by-doing in service work.

While prior learning-by-doing studies generally assume that workers can learn from their experience, they also argue that not all units of experience have an equal impact on workers' performance (e.g., Argote and Miron-Spketor, 2011; Lapre and Nembhard, 2010; KC and Staats, 2012). One important factor leading to such differences is the relatedness of workers' experience, which is the degree of similarity between workers' prior tasks and their current task[2]. Although researchers have investigated how focal and related experience affects workers' performance differently, they tend to define relatedness by simply considering the current task as focal and categorizing everything else as "related" (KC and Staats, 2012). However, different tasks may have different levels of relatedness to the current task, especially when the task is complex and can be characterized by multiple attributes. In the context of customs processing, customs declarations can be either import or export, and they can also include different types of goods. For example, consider

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[2] Relatedness is different from variety, which is usually measured in the literature by the Herfindahl-Hirschman Index (KC and Staats, 2012; Narayanan, Balasubramanian, and Swaminathan, 2009). Variety focuses more on the workers' experience portfolio itself, while relatedness further compares the workers' experience portfolio to their current task. For example, assume we have two workers whose next tasks are both task A. Worker 1 has done 20 task A and 80 task B before, and worker 2 has done 80 task A and 20 task B before. The variety of worker 1 and worker 2 will be the same ($0.2^2+0.8^2=0.68$), but the relatedness for worker 1 and worker 2 will be different (0.2 for worker 1, and 0.8 for worker 2).

a customs agent who is processing an import customs declaration for a food product. The customs agent has no experience in processing an import customs declaration for a food product, but has processed both exports and imports of chemical products. Compared to an export declaration of chemical products, an import declaration of chemical products may be more related to an import declaration of food. Hence, it is natural to assume that the agent's experience with the two declarations of chemical products could have a different impact on their performance on the import declaration of food, and simply classifying both types of experience as related experience may ignore this difference.

In this study, we seek to examine the role of experience relatedness on workers' performance and how the impact differs under different levels of experience. We separate the relatedness of workers' experience to their current tasks from the level of workers' experience, and then examine the impact of both on workers' performance. We argue that the relatedness of workers' experience can have differential effects on their skills and motivation for their current tasks, and their skills and motivation will have a joint impact on their performance. Higher relatedness usually implies that more skills accumulated by the workers are applicable to the current task (KC and Staats, 2012). On the other hand, too much relatedness or too little relatedness can both have a negative impact on workers' motivation. Too much relatedness leads to boredom and relaxation, while too little relatedness brings in worry and anxiety (Csikszentmihalyi, 1997). Further, the impact of relatedness may differ under different levels of experience, as the level of experience can affect the amount of skills accumulated and the impact of relatedness on motivation. The impact of relatedness can also vary for different performance measures, as different performance measures may rely on different levels of skills and motivation. Thus, we are motivated to examine the following research questions: First, how does the relatedness of workers' experience to their current tasks affect their performance? Second, how does the impact of workers' experience relatedness vary when they accumulate different levels of experience? Third, will the impact of workers' experience relatedness differ for different performance metrics, such as their efficiency versus quality?

Our setting enables us to evaluate the impact of workers' experience relatedness. First, the task itself involves a significant amount of knowledge work and can be characterized from multiple dimensions. Each dimension involves similarities and differences in the policies, procedures, and knowledge required for the task. In Costa Rica, customs declarations can be categorized into different "regimes" based on the direction of flow of goods and the associated tariff policy. The regimes include import, transit, export, and free trade zone[3]. For different regimes, customs agents usually need to follow different policies and procedures to complete the declaration. In addition, their work can also differ when the declaration is submitted to different customs houses, is processed for different importers or exporters, or involves different types of goods. Thus, it is hard to find two tasks that are exactly the same, and experience relatedness can play an important role in driving the workers' performance. To address those issues, we adopt an innovative approach to construct a continuous measure to evaluate the relatedness of customs agents' experience to their current task. We identify the facets describing the tasks, and calculate the relatedness of agents' experience for each of the individual facets. Then we create a composite index to capture the overall relatedness. Compared with prior research, our measure is more informative, because it considers experience relatedness from different dimensions, and also incorporates the measure of relatedness between different types of

[3] Customs regimes include: import - to bring in goods into ports of the country; export - to ship goods out of ports of the country; transit - to circulate goods from one port to another; free trade zone, a specific regime of import, under which importers enjoy 100% exemption from taxes and customs duties.

tasks in those dimensions (e.g., the relatedness between import customs declarations and export customs declarations).

We use the traditional learning curve model with agent fixed effects to investigate the impact of customs agents' levels of experience and experience relatedness on their performance, including their completion time in processing a customs declaration using a customs automation system and their quality of declaration processing. We collect detailed customs declaration data in Costa Rica over a five-year time period, and analyze import data at the largest customs house to test our research hypotheses. We use the import customs declaration as our unit of observation, and the data include 998,258 observations of 342 import agents' customs declaration records. In our analysis, we also control for the impact of other declaration-specific characteristics on the performance measures.

There are three key sets of results. First, we demonstrate that only accumulating greater levels of experience may not be enough to improve customs agents' performance. While agents' time to complete processing customs declarations decreases as their experience increases, their quality of processing does not improve. Second, we find that relatedness of customs agents' prior experience has a significant impact on their performance, and the impact follows different patterns for completion time and quality. As customs agents' experience relatedness increases, their completion time first decreases. However, after their experience relatedness reaches a certain level, their completion time starts to increase. On the other hand, an increase in the customs agents' experience relatedness is always associated with a decline in the probability of inspection, which implies a better declaration processing quality. Third, we further find that the impact of experience relatedness is stronger when customs agents accumulate more experience. We discuss the results and also conduct several additional analyses to evaluate the validity and robustness of our results.

This study has several contributions. Our study contributes to the discussion on the role of experience relatedness in learning curves and performance, which has recently received growing interest in the literature (e.g., Boh et al., 2007; Mukhopadhyay, Singh, and Kim, 2011; Narayanan et al., 2009; Staats and Gino, 2012). We show that experience relatedness has a significant impact on workers' performance, and the pattern of impact differs for different performance measures. This result is likely because experience relatedness has different effects on two important performance drivers – skills and effort (or motivation), and those two drivers also have different impacts on different performance measures. We also demonstrate that the impact of experience relatedness may depend on the amount of experience accumulated by the workers. Overall, our study responds to the call for more behavioral theory in operations management (Boudreau, Hopp, McClain, and Thomas, 2003; Gino and Pisano, 2008). Methodologically, we also offer an innovative approach to conceptualize and measure experience relatedness when the task and its related knowledge can be characterized in multiple dimensions.

2.2 Theory and Hypotheses

2.2.1 The Learning Curve Framework

In this study, we follow the literature on the learning curve framework as our baseline to model workers' learning-by-doing. Research on the learning curve has a long history. The earliest work can be traced back to Deway (1897) and early research focused on the education field. It was not until Wright's (1936) study of the cost-quantity relationship in aircraft manufacturing that the learning curve analysis was applied to firms.

Since then, research on organizational learning curves has been conducted in many industries (for example, Argote and Epple, 1990; Dutton and Thomas, 1984; Pisano et al., 2001). In addition, individual learning curve studies also started to change their focus to examine individuals' learning under various working conditions (for example, Nonaka, 1991; Reagans et al., 2005; Schilling, Vidal, Ployhart, and Marangoni, 2003; Shafer, Nembhard, and Uzumeri, 2001).

The classic form of the learning curve is as follows (Argote, 1999) [4]:

$$y = ax^{-b}$$

Where y is the outcome variable affected by the learning effects, x is the cumulative experience variable, and b is the learning rate. Outcomes can take a variety of forms, such as efficiency (Pisano et al., 2001), quality (Levin, 2000), and customer dissatisfaction (Lapre and Tsikriktsis, 2006).

Researchers have also attempted to extend the classic model in various directions. For example, Thompson (2007) and Boone et al. (2008) both attempted to incorporate organizational forgetting and the depreciation of knowledge into the learning curve model. Schilling et al. (2003) and Boh et al. (2007) sought to decompose experience into related and unrelated experience, and compare the impact of each on performance. Several other studies, such as Thornton and Thompson (2001) and Ramdas and Randall (2008), investigated the influence of learning curve spillovers. Most extensions of learning curve

[4] Typically, researchers use the logarithmic form of the equation: $\ln(y) = \ln(a)-b*\ln(x)$. With this transformation, the relationship between experience and outcome becomes linear and is more easily estimated than the classic nonlinear model.

studies have focused on explaining the variation in learning rates, such as Avgar, Tambe, and Hitt (2011), Pisano et al. (2001), Shafer et al. (2001), and Wiersma (2007).

2.2.2 Workers' Learning-by-doing

A basic proposition in the learning-by-doing literature is that individuals' experience with a certain task is positively associated with their performance on the task (e.g., Reagans et al., 2005; Yelle, 1979). As workers accumulate more experience, they can obtain more knowledge about the task, such as the steps to complete the task, the tools used, and the underlying principles for the task (Lapre and Nembhard, 2010). Some knowledge aspects may be codified, while other aspects can be more implicit, especially in knowledge work.

In the setting of customs processing, when customs workers are entering customs declaration data into customs automation systems, they need to learn the steps to collect and interpret the original documents, to understand how to complete the appropriate forms, and to attach corresponding approval requests. They also need to learn how to use the system, including how to log into the system, how to enter information, and how to upload documents. Further, they need to select the most appropriate tariff code for the merchandise to enter into the system. As there is little standardization on the selection of tariff codes, workers usually use principles developed from their repeated performing of the task to make their decisions. Overall, all those types of knowledge can help to improve the workers' performance in the tasks (Argote, 1999). Thus, following the literature on learning curves, we have our first baseline hypothesis:

H1: The level of workers' experience in the task has a positive impact on their performance.

2.2.3 Experience Relatedness and Workers' Performance

While the *level* of workers' prior experience can affect their performance, the impact of different *types* of experience may not be equal. One important factor affecting the impact of experience on workers' task performance is the relatedness of their experience to the current task. In a laboratory study, Schilling et al. (2003) found that students learned more quickly from related tasks than from the same task. However, field studies have shown different results. Boh et al. (2007) proposed that individual software developers gained more benefits from their experience in the same system than in related systems. Staats and Gino (2012) found that same-task experience was related to a larger improvement in performance than related-task experience in the short term, but in the long term related-task experience could bring greater benefit. KC and Staats (2012) demonstrated that surgeons' focal experience in a complex procedure was more beneficial than their related experience, because knowledge gained from focal experience was more applicable. Clark, Huckman, and Staats (2012) also stated that individual workers benefited more from their experience with the same client in the same domain than from their experience with other clients or in other domains, as there were more relation-specific assets developed between the worker and the client when client-domain experience increased. Nonetheless, those studies typically treat experience relatedness as dichotomous: experience is either related to the current task or it is not. In practice, tasks are usually very complex and have multiple dimensions along which experience can accumulate. For example, in customs work, customs declarations differ by type of goods, client and regime, as well as other factors, and levels of knowledge and experience could differ on these dimensions. Different levels of experience relatedness can have different impacts on their performance in the current task.

Staw (1980) stated that task performance is a joint function of skill and effort. Prior literature shows that workers with experience that is more related to the current task will be more familiar with the current task, thus having a better understanding of it and a better view of how to improve it (Bohn, 2005; Bohn and Lapre, 2011). For example, in the context of entering customs declarations data, workers can draw on their knowledge of prior declarations containing similar kinds of goods to make tariff codes justifications for the current declaration. However, it is more difficult to apply knowledge from prior declarations with goods that are very different. Overall, higher relatedness of prior experience to the current task is related to more skills applicable on the current task.

On the other hand, the relatedness of workers' prior experience to the current task may not be linearly related to their effort or motivation. Psychological studies suggest that the appraisal of novelty in a task is an important factor driving interest and motivation (Hackman and Oldham 1975, 1976; Silvia, 2006). Lack of novelty will eventually lead to boredom and relaxation, which reduces the workers' motivation and involvement in the tasks (Csikszentmihalyi 1975, 1990, 1997). Hence, if the current task is too much related to the worker's prior experience, it may decrease her feeling of novelty as well as her motivation in the current task. For instance, a customs agent who processes only import declarations may become bored if incoming import declarations are too similar or too related to what she has done before. The agent may approach the task in a more relaxed way and may not feel motivated to focus on the task and improve performance. However, too much novelty can also introduce worry and anxiety, and in turn decreases motivation (Csikszentmihalyi, 1997; Silvia, 2003). When current tasks are too much unrelated to the worker's prior experience, there may be excessive novelty which thus lowers the worker's motivation. A customs agent may feel a customs declaration she has never done before (i.e., not related to her experience at all) is too difficult, and she will worry about how to complete the task and indeed become less motivated. Overall, the worker's motivation in the current task will be the highest when it has a moderate level of relatedness to her prior experience. Too much relatedness and too little relatedness will both lead to a lower level of motivation.

Concluding the arguments above, we argue that the overall impact of workers' experience relatedness on their performance will follow an inverted-U shape. Figures 2.1 depicts the overall relationships between workers' experience relatedness and their skill, motivation and performance, respectively. As shown in the figure, when the level of experience relatedness is very low, both skill and motivation will increase as relatedness increases and the workers' performance will also improve. After relatedness reaches some point, motivation starts to decrease. When the decrease of workers' motivation outweighs the increase of workers' skills, the workers' performance will start to decline.

Accordingly, we propose that:

H2: The relatedness of workers' prior experience to the current task exhibits an inverted-U relationship with their performance, such that workers' performance initially improves with a higher level of experience relatedness, but eventually declines.

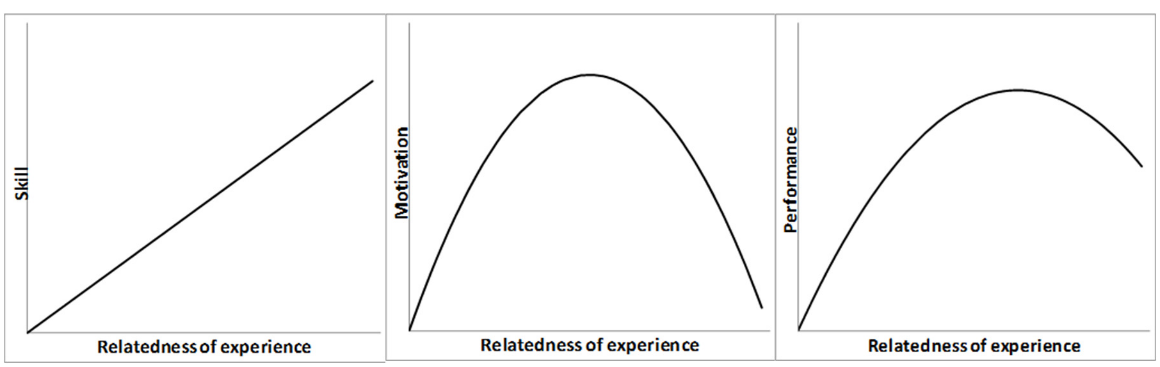

Figure 2.1: Experience Relatedness, Workers' Skill, Motivation, and Performance

Further, the impact of experience relatedness may differ under different levels of workers' experience. The acquisition of skills and knowledge is a process of accumulation (Newell and Rosenbloom, 1981). Thus, under higher levels of experience, workers with experience that is highly related to the current task accumulate more skills applicable than under lower levels of experience. In contrast, workers with experience that is highly unrelated to the current task also accumulate more skills under higher levels of experience, but the skills are mostly inapplicable to the current ask. Thus, they may not accumulate more skills applicable to the current task. For example, when customs agents have more experience, those who primarily do import declarations will have more skills in import declarations, but those who primarily work on export declarations will not have more skills on import declarations, because the skills they accumulated are mostly for export declarations. Therefore, when customs agents' level of experience is higher, the difference in skills for the import declarations between agents who primarily process import declarations and those who mainly work on export declarations will be even greater. Overall, this suggests that the impact of workers' experience relatedness on workers' skills will be stronger under higher levels of experience than under lower levels of experience.

Meanwhile, the lack of novelty in the current task will have a greater detrimental effect on motivation for workers with higher skills, because it will lead to more boredom and relaxation (Csikszentmihalyi, 1997). As argued earlier, when workers accumulate higher levels of experience, those workers with higher experience relatedness will have many more applicable skills than workers with lower experience relatedness. Hence, the impact of lack of novelty on workers' motivation will be larger for workers with higher levels of experience than for workers with lower levels of experience. For example, an experienced customs agent whose experience is mostly with import declarations may feel a new import declaration is more boring than an experienced agent who works primarily on export declarations, because she has more skills in processing import customs declarations and may be more saturated with her performance. On the other hand, a new customs agent who primarily processes import declarations may have a similar level of motivation on a new import declaration as a new agent who works mainly on export declarations, as both agents are new to the field, and have accumulated few skills on import declarations. Overall, the relatedness of workers' experience will also have a stronger effect on their motivation under higher levels of experience.

As the impact of experience relatedness on both skill and motivation will be greater under higher levels of experience, we expect that the overall impact of experience relatedness on performance will also be greater. This implies a steeper inverted-U shape under higher levels of experience. Figure 2.2 depicts this relationship. As can be seen in Figure 2.2, when workers' experience relatedness is very low, their performance will improve faster under higher levels of experience, because their skills applicable to the current task will increase more. When workers' experience relatedness is very high, their motivation will drop more quickly under higher levels of experience. While workers' skills applicable to the current task also increase more, this effect will likely be dominated by the effect of the decline in their motivation. Overall, the workers' performance will also drop more under higher levels of experience. All in all, when the workers accumulate higher levels of experience, their experience relatedness will be associated with a greater improvement in their performance at the beginning, but will eventually be related to a greater decline. Therefore, we hypothesize:

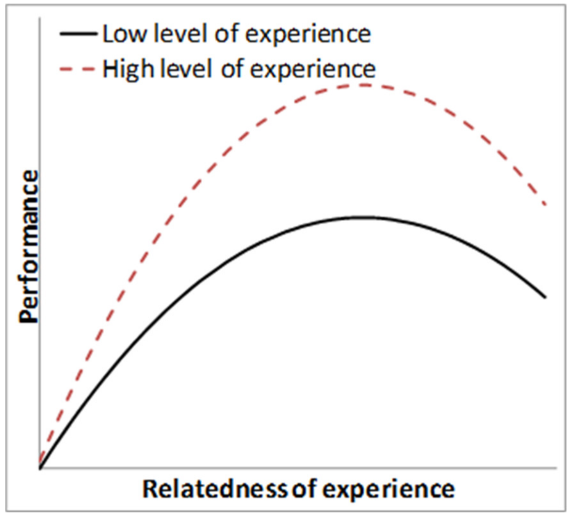

Figure 2.2: Experience Relatedness, Level of Experience, and Performance

H3: The inverted-U relationship between relatedness of workers' prior experience to the current task and their performance will be steeper for workers with a higher level of experience, such that workers' performance will initially improve more with increasing values of relatedness, but will also decline more steeply.

2.3 Research Setting

Our research setting is customs processing in the country of Costa Rica. This setting affords an ideal opportunity to investigate learning curves of workers and the role of their experience relatedness. The customs industry is in the services field, and requires significant knowledge work. Customs agents must hold a degree to become eligible for work, so not everyone can become a customs agent. Only those who have the essential knowledge to perform the tasks can work in this area. Another important aspect is that Costa Rica implemented a customs automation system in 2005 to standardize their customs processes, and our data collection started from that time. The system changed the entire process and the associated customs policies dramatically, and all customs agents must use this system to process customs declarations. This helps us to avoid the potential bias from unobserved customs agents' experience before the implementation of the system, because due to the changes with the new system, experience prior to the system is mostly irrelevant. In addition, there are consistent work units in the setting: customs declarations. As the format of customs declarations is generally the same, the learning-by-doing effect may be quite salient in this setting. On the other hand, customs declarations can vary significantly with respect to their details, including the regimes to which the declarations belong, the customs houses where the declarations are submitted, the size of clients (importers or exporters), and the type of goods involved in the declarations. In this setting, the extent of experience relatedness may play an important role in determining the workers' performance on those declarations, because every task can be related with prior tasks in certain aspects. For example, an agent who works on an import declaration of food at the customs house located on the Nicaragua border for a large importer may have processed different amounts of other import declarations, declarations at the customs house at the Nicaragua border, declarations for large importers, or declarations that include food products.

In the following sections, we discuss the context of Costa Rican customs, the primary group of workers in our research – customs agents, and the customs declaration process.

Customs in Costa Rica. Costa Rica is located in Central America, bordered by Nicaragua to the north, Panama to the east and south, the Pacific Ocean to the west and south and the Caribbean Sea to the east. It has multiple ways to connect with foreign countries, such as by air, by sea, and by land. As a result, the Costa Rican economy relies heavily on its international trade.

As shown in Figure 2.3, the country has established multiple customs houses[5]: two customs houses at the Nicaragua and Panama borders, one customs house at a major port on the Pacific Ocean, one customs house at a major port on the Caribbean Sea, one customs house at the main airport, and one central customs house. The main airport customs house is the most important one, because it processes the majority of customs declarations for the country in terms of both volume and value of goods.

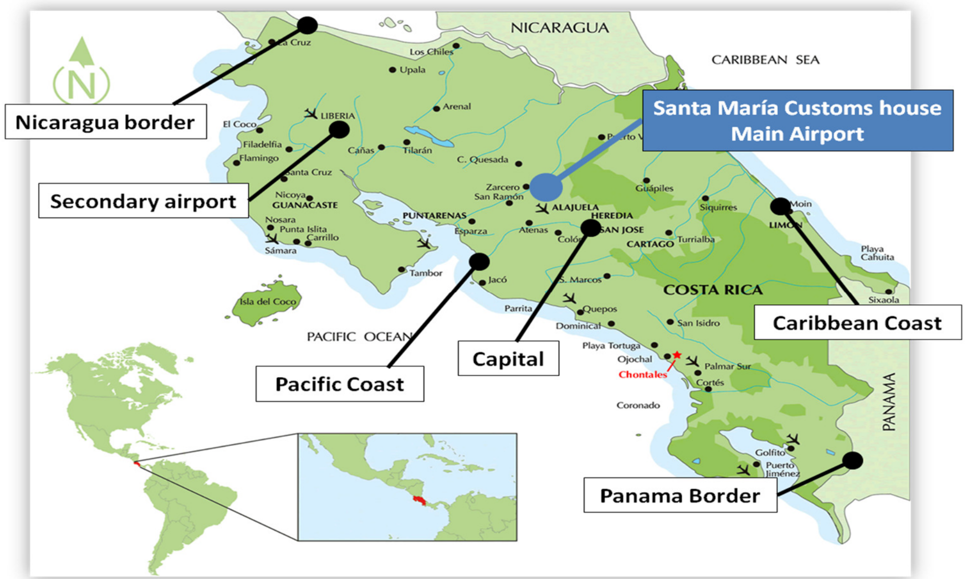

Figure 2.3: Customs Houses in Costa Rica

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[5] A Customhouse is a building housing the offices for the government officials who process the paperwork for the import and export of goods into and out of a country.

Customs agents. Customs agents are individuals who are registered to perform customs declaration work. Their major duties include document preparation, payment of customs duties, and communication with customs inspectors. As we learned in our interviews with an importer, importers and exporters in Costa Rica always hire a customs agent to process customs declarations on their behalf; given the specialized knowledge and training required for customs work, it is much easier and more efficient for firms to hire customs agents than to do this work themselves. Thus, although an information system was implemented to offer importers and exporters the opportunity to process customs declarations themselves, our interviews indicated that they do not do so. Thus, the role of customs agents is still very important in the field.

Costa Rica has strict requirements for customs agents. From Acts 29 and 34 of the law of Costa Rican customs[6], licensed customs agents should have a Bachelor's degree in Customs administration or equivalent degrees in Law, International Business, or Public Administration, or approval of proficiency tests in the customs area. Our interviews suggest that the actual requirements are even stricter, as the agents should obtain the Licentiate degree[7] after their Bachelor's degree, and they also need to fulfill the requirements of the

[6] This law is effective from June 2005. A detailed description of the law can be found at the following url: https://www.hacienda.go.cr/NR/rdonlyres/7F869F85-38E3-4720-8643-E3B52EAC4C3A/6909/LeyGeneraldeAduanas.htm.

[7] In Costa Rica, the title is awarded to students after five to six years of study (usually between three and four more semesters with courses after the completion of the bachelor's degree). Students are also required to write a thesis in some universities, attend a graduation seminar, or develop a project in order to graduate, while some degrees involve almost the same credits as a master's degree, the level of difficulty is not the same as graduate level work. The Consejo Nacional de Rectores (Council of Rectors) defines a licentiate as lower than a master's degree but higher than a bachelor's degree. See: https://en.wikipedia.org/wiki/Licentiate#Costa_Rica

association of professionals in Economics (*Colegio de Profesionales en Ciencias Económicas de Costa Rica*).[8]

In Costa Rica, customs agents are usually not specialized in certain regimes, customs houses, and types of goods. Agents process multiple types of declarations at the same time, and usually can work at multiple customs houses. They are also able to work with different clients for diverse types of goods. For example, we learned from interviews that many customs agents who process import customs declarations also perform other regimes of declarations, such as export, transit, or free trade zone.

Customs procedures. Currently, customs agents must submit declarations electronically via a customs automation system. The detailed process is outlined in Figure 2.4. To start, the customs agents have to collect the original documents about the declarations from the clients. Then they use interface software to communicate with the centralized system to get a unique ID number assigned to the declaration before entering other information, because this ID will be used in the following data entry process. Once connected to the system, they will see the screen with form templates and blank fields. They need to input information into the main declaration forms, item detail forms, shipments, and invoices. At the same time, they need to decide the best content to fill into the forms using those original documents from the clients. The agents also need to prepare approval requests when required. When they finish, they will submit the forms and approval requests to the central system. Then they will upload the attachments, such as the scanned copy of the original documents. After a very short period of time, the system will

[8] For a list of the requirements, please check: http://www.cpcecr.com/archivos-de-usuario/Ley7105.pdf

provide feedback with the channel assigned for the declaration. If the channel is “green”, the customs agents can directly go to the warehouse where the goods are stored and get them released. Otherwise, they have to take the physical documents to customs inspectors. When the channel is “red”, they also have to wait for the results of physical inspection of goods, which are communicated via the system. During the process, the system logs the time when an ID is assigned, when a channel is assigned, and when the goods can be released.

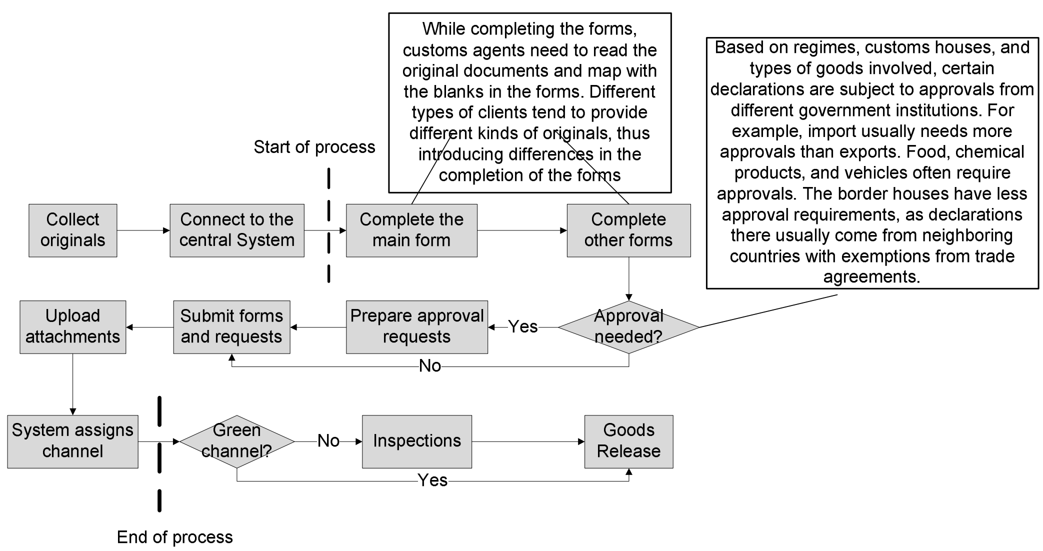

Figure 2.4: The Customs Declaration Process in Costa Rica

In this study, we focus on investigation of the customs agents’ performance in processing and submitting all channels of customs declarations to the system (i.e., the procedure from the creation of the declaration in the system to the assignment of channel)[9]. While the general steps to process the customs declarations are similar, there are also differences in the detailed procedures with regard to different declarations, as denoted in Figure 2.4. For example, some forms, items, or approvals may be required only for certain regimes, certain customs houses, or certain types of goods. Importing food at the port houses requires health approvals, while exporting food, importing clothes, or importing food at the border houses will not. The format of original documents can also be different across clients, which may lead to differences in the declaration processing procedures. Overall, our interviews suggested that agents must learn how to enter data into the customs automation system, what information and approvals are required for different types of commodities, and how to process originals from different types of clients. That knowledge can potentially influence the agents' performance in processing customs declaration with the system, such as time to complete and quality.

2.4 Data and Variables

2.4.1 Data

In this study, we analyze learning curves of customs agents processing import customs declarations at Santamaria, the largest customs house of the country in terms of transaction volume. To control for procedural differences across regimes, we choose the import regime as the focal task, because it is the primary customs regime with the largest

[9] Our performance measures focus on only the procedures till the assignment of channel. Specifically, we do not examine the customs agents' performance and learning in the inspection procedure for red and yellow declarations, because that includes the interactions between customs agents and government officials. It is hard to identify individual agents' learning-by-doing in the inspection procedures.

amount of transactions in Costa Rica. We also control for productivity differences across customs houses by focusing on declarations processed at the Santamaria customs house, as Santamaria is the most influential customs house in the country. Overall, the characteristics of our sample make it well suited for the goals of this study.

To understand the customs declaration processes, the work of customs agents, and the policies of the customs houses about customs declarations, we made three field trips conducting 19 interviews: seven with customs brokerage firms and their agents, two with importer firms, two with logistics firms, seven with government officials, and one with the manager of the software company providing the interface system for the customs automation system. We also conducted six conference calls with one brokerage firm and one importer to complement our interviews and resolve questions that emerged in our study. The interviews and conference calls were important in helping us to better understand the context and interpret our results.

Our empirical data source is the customs declaration data collected from the public website of the customs automation system. All declarations in our data are processed electronically via the customs automation system. Our data contains the names of the individual agents processing the declaration, basic characteristics of the declaration such as the customs house, channel, the client (importer or exporter), type of goods involved, monetary value and customs duty, and the different timestamps indicating stage of process. Our final sample contains all 998,258 import customs declarations processed by 342 different customs agents at the Santamaria customs house from March 2006 to June 2010.

2.4.2 Dependent, Independent, and Control Variables

Dependent Variables. To fully understand the impact of customs agents' learning-by-doing and experience relatedness on their operational performance, we investigate two performance measures about customs agents' declaration processing. This also responds to the call for understanding of performance from multiple dimensions (KC and Staats, 2012). Our first performance measure is the amount of time it takes to complete processing of a certain declaration. Past studies examining learning in the service context have often relied on similar types of indicators (e.g. Mukhopadhyay et al., 2011; Pisano et al., 2001; Reagans et al., 2005). Following the literature, we define this dependent variable, *TimeComplete*, as the time spent between the creation of the declaration in the system (indicated by the assignment of declaration ID) and the channel assignment for the declaration. Our interviews with several customs agents show that this time is commonly used to assess agents' performance in customs declarations.

Our second performance measure is a dummy variable *Inspection* to indicate whether the declaration is assigned with a red channel or not (i.e., requires physical inspection of goods). This measure evaluates the quality of customs declarations processing, as mistakes will be captured by the system and thus lead to physical inspections of the goods. As the physical inspection usually takes a long time (days or weeks), this measure is also considered as an important indicator of the agents' performance.

Independent Variables. Our experience variable, *Experience*, is measured as the cumulative number of all declarations processed via the customs automation system by the individual agent prior to processing the current declaration, which is similar to the cumulative output measure used in learning curve research on manufacturing and other industries (For example, Argote, 1999; Reagans et al., 2005). Although our Santamaria sample starts from March 2006, the agents' history of processing declarations is available in the system from July 2005.[10] Further, our interviews suggest that before the current system, customs declarations were processed in very different ways, so the agents' experience accumulated before the implementation of this system may not be relevant. As a result, we construct our experience variable for the agents from July 2005 onwards. Our data construction is motivated by similar approaches used in the learning curve literature.

To measure the relatedness of agents' prior experience with the current task, we adopt an innovative approach. As our task involves knowledge about multiple dimensions, we first identify those dimensions based on the interviews, namely the regime, the customs house, the client, and the sector of goods. We also identify the variables representing each of those dimensions. After that, we choose appropriate relatedness measures for each of those dimensions. For example, if the dimension is indicated by a vector of binary variables, we can choose the Jaccard Index (Jaccard, 1901); if the dimension is identified by a categorical variable, we can select context-based continuous variables to construct the Euclidean distance between different values for the variable, and then convert the distance to relatedness. We then calculate the dimension-specific relatedness between the current task and each of the prior tasks processed by the agent, and average them for all prior tasks. Finally, we treat the dimension-specific average relatedness obtained in the prior step as variables describing the agents' prior experience, and then calculate its distance from the

[10] The import regime was implemented first at the Pacific Coast customs house -- Caldera in July 2005. Santamaria implemented the import regime in March 2006.

current task with all variables equal to one. The resulting distance is then converted to a Relatedness Index again, which ranges from zero to one. Detailed procedures to generate this variable are described in the Appendix A.

Below is an example of a calculation of the Relatedness Index for two customs agents whose current tasks are the same: an import declaration at the Santamaria customs house for a large client, which includes both food and vegetable products. Table 2.1 summarizes the two agents' experience portfolio on the four dimensions, and gives the levels of relatedness between different values for each of the four dimensions. Based on that information, we can then calculate the dimension-specific relatedness and the overall relatedness to the current task for the two agents.

Table 2.1: Experience Mix of Two Customs Agents and Relatedness Indices[11]

Description of experience portfolio (in terms of #declarations processed)					
	Level of experience	Regime	House	Client type	Sector of goods
Agent 1	100	80 import 20 export	20 at Santamaria 80 at Capital	90 for large client 10 for small client	20 food 20 animal 30 food and vegetable 30 food and animal
Agent 2	200	40 import 160 export	180 at Santamaria 20 at Capital	100 for large client 100 for small client	10 food 15 animal 160 food and vegetable 15 food and animal

Relatedness between categorical values in regime, house, and client type			
	Import and Export	Santamaria and Capital	Small and Large
Relatedness	0.2	0.6	0.05

[11] The values presented in Table 1 are fictitious and are not real values in our sample. The level of experience refers to the total amount of declarations processed by the agent prior to the current task.

For agent 1, regime relatedness equals (80*1+20*0.2)/100=0.84, house relatedness equals (20*1+80*0.6)/100=0.68, and client relatedness equals (90*1+10*0.05)/100=0.905. To calculate the sector relatedness, we compute the Jaccard Index. The current task includes food and vegetable, thus it will be represented by a vector of binary variables among which the two variables for food and vegetable equal to 1. For declarations with only food, the Jaccard Index will be 1/2, as only one variable matches among the possible two. For declarations with only animal, nothing matches and the Jaccard Index will be 0. For declarations with food and vegetable, both sectors match and the Jaccard Index will be 1. For declarations with food and animal, the Jaccard Index will be 1/3, because one sector food matches among the possible three: food, vegetable, and animal. Overall, for the current task, sector relatedness equals (20*1/2+20*0+30*1+30*1/3)/100=0.5. The overall relatedness will be $\frac{2-\sqrt{(1-0.84)^2+(1-0.68)^2+(1-0.905)^2+(1-0.5)^2}}{2-0} = 0.689$

Similarly, we can calculate the corresponding relatedness values for agent 2. For this agent, regime relatedness is (40*1+160*0.2)/200=0.36, house relatedness is (180*1+20*0.6)/200=0.96, client relatedness is (100*1+100*0.05)/200=0.525, and sector relatedness is (10*1/2+15*0+160*1+15*1/3)/200=0.85. Thus, the overall relatedness for agent 2 will be $\frac{2-\sqrt{(1-0.36)^2+(1-0.96)^2+(1-0.525)^2+(1-0.85)^2}}{2-0} = 0.594$

Figure 2.5 depicts the dimension relatedness values of customs agent 1 and customs agent 2.

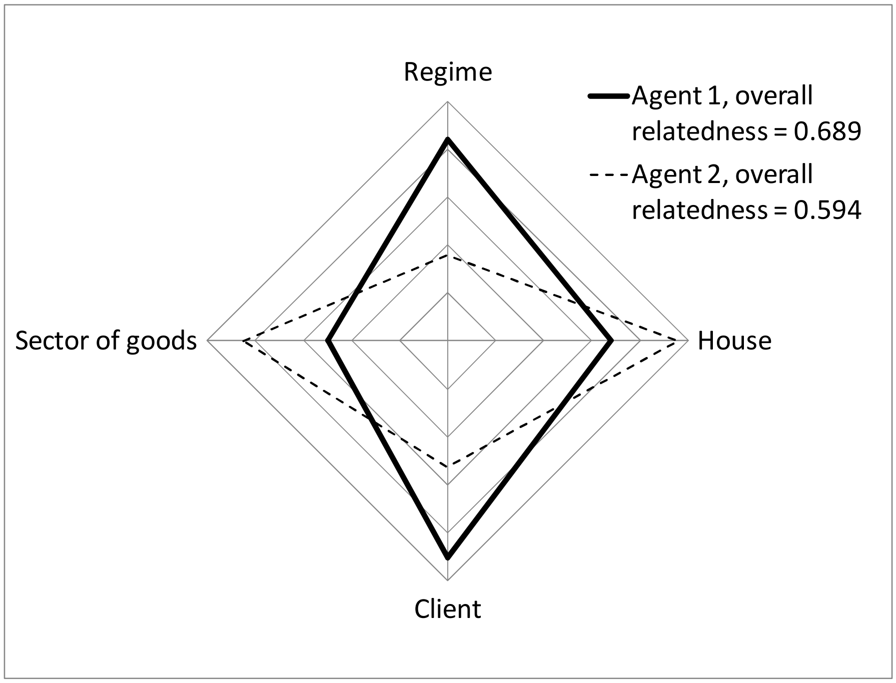

Figure 2.5: Dimension Relatedness and Overall Relatedness

Control Variables. We also include several control variables in our regressions. There are several common factors that will affect both the time to complete and the likelihood of inspection. When a customs declaration includes certain types of goods (e.g. chemical products), it may require preparation of additional documents and take more time. In addition, this can also affect the risk level of the declaration and lead to more inspection. To control for this factor, we define a vector of 16 dummy variables *Sector,* indicating whether a specific sector of goods (for example, foodstuffs or textiles) is included in the declaration. As we are able to observe the tariff codes of goods included in the declaration, we adopt the harmonized system codes to categorize them.[12]

[12] See http://www.foreign-trade.com/reference/hscode.htm for detailed definition of sectors.

The time to complete declaration processing and the likelihood of inspection can also be related to the complexity and significance of the declaration, because declarations with higher complexity and significance may require special attention and greater effort for customs agents. We define two variables to control for that. *Line* is the number of lines of goods in the declaration, which measures the complexity of the declaration. *Value* is the value of goods in the declaration, which measures the importance of the declaration. In our data, the value of goods is always measured in dollars.

Our interviews with customs agents suggest that the agents' efficiency is also highly correlated with the workload of the agents. Recent research indicates that workers' workload can significantly affect their service time (KC and Terwiesch, 2009). We introduce a continuous variable *AgentWorkload* to control for this. *AgentWorkload* is the total number of customs declarations processed by a certain customs agent in the same day, and it incorporates all regimes of customs declarations.

We also notice that individual workers' efficiency may vary significantly within the week.[13] *Dayofweek* is a vector of dummy variables indicating the day of week that the declaration was entered, which controls for workload and productivity differences across day of week. Under our definition, Sunday is the baseline of *Dayofweek*.

Control Variables specific to time to complete. To control for technological improvement and other time-varying factors, *Year* is a vector of dummy variables indicating the year when the declaration was entered. As our data ranges from March 2006

[13] A variety of work has demonstrated variance in worker productivity across days of the week and hours of the day. See for example, Bryson and Forth (2007), and Yao, Dresdner, and Zhu (2010).

to June 2010, we include indicator variables of the last four years, and year 2006 is the baseline category.

In addition to the day of week, workers' time to process customs declarations may also vary significantly within a certain day. *Hour* is a vector of dummy variables indicating the hour that the declaration was entered, which controls for workload and productivity differences across time of day. Under our definition, 12:00 pm at midnight is the baseline of *Hour*.

We also notice from the interviews that several customs agents and managers complained that their performance always suffered a significant decline during the month after a new phase of system implementation was conducted, because people tended to send testing declarations and the system was congested. To measure the implications of these systems implementations, we create a vector of dummy variables *ImplementationCongestion*. We set the variables to one when the focal declaration is submitted within one month after a new phase of system implementation, and zero otherwise.[14] Moreover, to fully control for the impact of system congestions on completion time, we also include a continuous variable *SysWorkload* in our regressions. *SysWorkload* is the total number of customs declarations processed in the system during the same hour. Similar to *AgentWorkload*, it also incorporates all regimes of customs declarations.

Control Variables specific to inspection. A decision to inspect the physical goods is an important indicator of the quality in the agents' completion of declaration processing.

[14] The new phase of system implementation can be the implementation of a new regime, and can also be the implementation of an existing regime at a new customs house.

However, several other factors can also influence this decision. Our interviews suggest that it also depends on the history of the agents, of the brokerage firm where the agents are employed, and of the client. As a result, we include three continuous variables to control for historical factors. *AgentHistory* is calculated by the ratio of red declarations to all declarations processed by the focal agent in the past 60 days. Similarly, we calculate *BrokerHistory* and *ClientHistory* using the ratio of red declarations to all declarations from the focal broker or the focal client in the past 60 days.

Further, there are also yearly and seasonal differences in the overall inspection rate. Hence, we include another continuous variable *OverallInspectionRate* calculated by the ratio of red declarations to all declarations for all agents in a certain month. It helps to capture the impact of overall inspection rate on the inspection decision over a certain declaration.

Research Models. We follow the traditional log-linear learning curve models adopted in the literature (e.g., Adler and Clark, 1991; Argote, 1999; Reagans et al., 2005; Thompson, 2007). For time to complete and quality, we first estimate a quadratic model for the relatedness of experience. For agent *i* and customs declaration *d*, the regression models we estimate are:

$$Log(TimeComplete_{id}) = \beta_0 + \beta_1 Log(Experience_{id}) + \beta_2 Relatedness_{id} + \beta_3 Relatedness_{id}^2 + \beta_4 Relatedness_{id} * Log(Experience_{id}) + \beta_5 Relatedness_{id}^{\,2} * Log(Experience_{id}) + \beta_6 Sector_d + \beta_7 Log(Line_d) + \beta_8 Log(Value_d) + \beta_9 Log(AgentWorkload_{id}) + \beta_{10} Dayofweek_d + \beta_{11} Year_d + \beta_{12} Hour_d + \beta_{13} ImplementationShock_d + \beta_{14} Log(SysWorkload_d) + \gamma_i + \varepsilon_{id} \quad \text{-----[2.1]}$$

$$Inspection_{id} = \beta_0 + \beta_1 Log(Experience_{id}) + \beta_2 Relatedness_{id} + \beta_3 Relatedness_{id}^2 + \beta_4 Relatedness_{id} * Log(Experience_{id}) + \beta_5 Relatedness_{id}^{\,2} * Log(Experience_{id}) + \beta_6 Sector_d +$$

$\beta_7 Log(Line_d) + \beta_8 Log(Value_d) + \beta_9 Log(AgentWorkload_{id}) + \beta_{10} Dayofweek_d +$

$\beta_{11} AgentHistory_{id} + \beta_{12} BrokerHistory_d + \beta_{13} ClientHistory_d + \beta_{14} OverallInspectionRate_d$

$+\gamma_i + \varepsilon_{id}$ -----*[2.2]*

For comparison, we also estimate a linear model by dropping the quadratic terms (i.e., $Relatedness_{id}^2$ and $Relatedness_{id}^2 * Log(Experience_{id})$). In the equations, γ_i is the agent fixed-effect and ε is the standard error. We estimate this regression using fixed effects panel data methods to control for the effects of customs agents' ability on their performance. In our analyses, we use heteroskedastic robust standard errors clustered by agents. In our robustness checks, we also include results using GLS estimation and panel heteroskedastic and AR(1) or PSAR(1) structure for the error terms.

One issue in the model on *Inspection* is that the dependent variable is a binary variable, which may suggest the use of discrete choice models, such as logit or probit regressions. However, according to the discussion from Ai and Norton (2003), it is very difficult to interpret and make inferences for the moderation effects in logit and probit models, especially when we also need to estimate fixed-effects. In such models, the significance of the interaction effect cannot be tested with a simple t-test on the coefficient of the interaction term, and the interaction effect is conditional on the values of the independent variables. Therefore, the sign of the coefficient of the interaction term does not necessarily indicate the sign of the interaction effect. In addition, the estimation of conditional fixed-effects models with interactions also has problems. Hence, we use the linear probability model instead. We also conduct robustness checks using conditional fixed-effect logit models, and the signs and significance of the coefficients remain consistent.

2.5 Results

2.5.1 Estimation Results and Tests of Hypotheses

Table 2.2 and 2.3 contain the descriptive statistics for our data, and Table 2.4 and 2.5 present our main estimation results.

Table 2.2: Descriptive Statistics for Time Regression

	Variable	Mean	Std. Dev.	1	2	3	4	5	6
1	**Log(TimeComplete)**	2.958	1.191						
2	**Log(Experience)**	8.289	1.445	-0.189					
3	**Relatedness**	0.555	0.109	0.076	-0.205				
4	**Log(Line)**	1.583	1.131	0.009	-0.048	-0.091			
5	**Log(Value)**	7.720	1.913	0.060	0.008	0.033	0.378		
6	**Log(AgentWorkload)**	3.056	1.222	-0.149	0.663	-0.281	-0.116	-0.073	
7	**Log(SysWorkload)**	5.158	0.740	0.035	0.210	-0.137	-0.026	0.030	0.020

Table 2.3: Descriptive Statistics for Inspection Regression

	Variable	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9
1	**Inspection**	0.129	0.335									
2	**Log(Experience)**	8.289	1.445	0.075								
3	**Relatedness**	0.555	0.109	-0.105	-0.205							
4	**Log(Value)**	1.583	1.131	0.292	-0.048	-0.091						
5	**Log(Line)**	7.720	1.913	0.183	0.008	0.033	0.378					
6	**Log(AgentWorkload)**	3.056	1.222	-0.013	0.663	0.281	-0.073	-0.116				
7	**AgentHistory**	0.141	0.133	0.371	0.212	-0.164	0.074	0.124	0.011			
8	**BrokerHistory**	0.140	0.120	0.330	0.258	-0.103	0.072	0.081	0.073	0.902		
9	**ClientHistory**	0.117	0.198	0.381	0.130	-0.096	0.143	0.214	0.017	0.506	0.432	
10	**OverallInspectionRate**	0.131	0.048	0.141	0.484	0.050	0.037	0.027	0.079	0.344	0.371	0.197

Table 2.4: Main Estimation Results: Time to Complete

DV: log(TimeComplete)	(1) Controls only	(2) Learning	(3) Linear model of Relatedness	(4) Linear model with interactions	(5) Quadratic model of Relatedness	(6) Quadratic model with interactions
Log(Line)	0.0144^{*}	0.0143^{*}	0.0152^{*}	0.0155^{*}	0.0152^{*}	0.0156^{*}
	(0.0058)	(0.0058)	(0.0060)	(0.0060)	(0.0059)	(0.0059)
Log(Value)	0.0278^{***}	0.0228^{***}	0.0228^{***}	0.0229^{***}	0.0216^{***}	0.0210^{***}
	(0.0039)	(0.0039)	(0.0039)	(0.0039)	(0.0038)	(0.0037)
Log(SysWorkload)	-0.0256^{+}	-0.0171	-0.0171	-0.0170	-0.0172	-0.0161
	(0.0148)	(0.0144)	(0.0144)	(0.0144)	(0.0144)	(0.0143)
Log(AgentWorkload)	0.0847^{***}	0.1008^{***}	0.1009^{***}	0.1031^{***}	0.0993^{***}	0.1020^{***}
	(0.0236)	(0.0229)	(0.0229)	(0.0228)	(0.0229)	(0.0227)
Log(Experience)		-0.0696^{***}	-0.0690^{***}	-0.1205^{***}	-0.0678^{***}	-0.0053
		(0.0136)	(0.0134)	(0.0334)	(0.0136)	(0.0472)
Relatedness			0.0893	-0.6747	-1.2222^{***}	1.4175^{+}
			(0.1262)	(0.4737)	(0.3419)	(0.7399)
Relatedness^2					1.1582^{***}	-2.0765^{*}
					(0.2931)	(0.8375)
Relatedness * Log(Experience)				0.0944		-0.3722^{***}
				(0.0596)		(0.1026)
Relatedness^2 * Log(Experience)						0.4414^{***}
						(0.1150)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	998,258	998,258	998,258	998,258	998,258	998,258
R-square (within)	0.0774	0.0784	0.0784	0.0786	0.0786	0.0791
R-square (overall)	0.0645	0.0785	0.0789	0.0795	0.0786	0.0797

1. Numbers in parentheses are robust and cluster standard errors.
2. $^{+}$ $p<0.1$; * $p<0.05$; ** $p<0.01$; *** $p<0.001$.
3. Coefficients for dummy control variables are unreported.

Table 2.4 reports the estimation results for the model of time to complete. The first column reports the coefficients for the model only with control variables. As we see in the table, the coefficients of *Log(Line)* and *Log(Value)* are both positive and significant at the 0.05 level. Thus, the number of lines and the value of goods contained in a declaration are positively associated with the time it takes to process a customs declaration. In addition, we find that the agent workload is positively related with the time it takes to process a declaration, but the system workload is not. Although not reported in the table due to space constraints, we also include sector, year, day of week, hour, and implementation congestion dummy variables in the regressions.

Column 2 in Table 2.4 adds the experience variable. Columns 3-4 report the estimation results on the linear model of relatedness, while Columns 5-6 report the estimation results on the quadratic model of relatedness. We notice that the coefficients of the linear specification are not significant, while the coefficients of the quadratic specification are significant. Thus, in this setting, the impact of relatedness on agents' time to process the customs declaration follows a quadratic relationship.

To evaluate our hypotheses, we followed the standard statistical procedure (e.g., Greene, 2003) to test the main effects in the full model (appearing in Column 6 of Table 2.4). This requires differentiating equation [2.1] with respect to the particular effect and substituting the mean of the moderator variables in the expression.

The marginal effect for *Log(experience)* is -0.0707 and is significant at the 0.001 level. Thus, H1 is supported for time to complete. The effect indicates that when the experience of a customs agent doubles, the time it takes to process a customs declaration by this agent decreases by 4.78%.[15] According to prior learning curve studies, this number is 20% on average for workers in manufacturing industries (Argote and Epple, 1990; Dutton and Thomas, 1984), and 8% on average for workers in other service industries (Pisano et al., 2001; Reagans et al., 2005). As a result, our results suggest that the learning rate of customs agents is relatively lower than that of workers in other settings that have been studied. Equivalently, our learning rate implies a 36.04% performance improvement for an agent during the first year of study.[16]

The marginal coefficient of *Relatedness* is negative and significant ($\beta = -1.6680$, $p < 0.001$), and the marginal coefficient of *Relatedness*^{2} is positive and significant ($\beta = 1.5826$, $p < 0.001$). The customs agents' time to complete declaration processing reaches its minimum when *Relatedness* equals 0.5270, which is slightly below the mean of *Relatedness* in the sample. The time to complete declaration processing will first decrease and then increase with increases in *Relatedness*. That indicates an inverted-U relationship of performance with regard to *Relatedness*, as more time to complete the task means worse performance. Therefore, H2 is supported for time to complete. We can also see that when experience is low (two standard deviations below the mean) and when experience is high (two standard deviations above the mean), the marginal coefficients of *Relatedness* and *Relatedness*^{2} still have the same signs as when experience is average, so the relationship is generally consistent across the range of values for experience.

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[15] $=1-2^{-0.0707}$

[16] The average number of declarations processed by a customs agent per year is about 556.67. The performance improvement for the first year is calculated by $1-556.67^{-0.0707}$.

Next, we find that the coefficient of *Relatedness*^{2} * *Log(Experience)* is positive and significant ($\beta = 0.4414$, $p < 0.001$). Following the approach in Slaughter, Ang, and Boh (2007), we examine the second derivative of *Relatedness* in [1] under a low level and a high level of *Log(Experience)*. When experience is low (two standard deviations below the mean), the value of the second-derivative is 0.6136; when experience is high (two standard deviations above the mean), the value becomes 5.7168. Thus, under a higher level of experience, the impact of relatedness will be stronger, as the rate of change is larger, and our H3 is also supported for time to complete.

Table 2.5 reports the results for the model of inspection. Similarly, Column 1 reports the coefficients for the model only with control variables, Column 2 adds the experience variable, Columns 3-4 present the results on the linear model of relatedness, and Columns 5-6 show the results on the quadratic model of relatedness. We observe that the coefficients of the linear specification are mostly significant, while the coefficients of the quadratic specification are not significant. Thus, under this circumstance, the impact of relatedness on agents' declaration processing quality may follow a linear relationship.

To evaluate our hypotheses, we again followed Greene's (2003) standard statistical procedure to test the main effects in the full model (appearing in Column 4 of Table 2.5). This time, we differentiate equation [2.2] (without the quadratic terms) with respect to the particular effect and substituting the mean of the moderator variables in the expression.

Table 2.5: Main Estimation Results: Inspection

DV: Likelihood of Inspection	(1) Controls only	(2) Learning	(3) Linear model of Relatedness	(4) Linear model with interactions	(5) Quadratic model of Relatedness	(6) Quadratic model with interactions
Agent History	0.4735***	0.4749***	0.4751***	0.4574***	0.4799***	0.4501***
	(0.0467)	(0.0469)	(0.0485)	(0.0459)	(0.0501)	(0.0461)
Broker History	0.0838+	0.0866+	0.0874	0.0980+	0.0865	0.1059*
	(0.0498)	(0.0502)	(0.0531)	(0.0504)	(0.0555)	(0.0511)
Client History	0.3283***	0.3283***	0.3313***	0.3308***	0.3302***	0.3286***
	(0.0206)	(0.0206)	(0.0203)	(0.0202)	(0.0202)	(0.0200)
Overall Inspection Rate	0.1633***	0.2076***	0.1909***	0.1874***	0.1885***	0.1924***
	(0.0289)	(0.0345)	(0.0345)	(0.0360)	(0.0346)	(0.0367)
Log(Experience)		-0.0030*	-0.0015	0.0169**	-0.0014	-0.0101
		(0.0015)	(0.0016)	(0.0058)	(0.0016)	(0.0082)
Relatedness			-0.1807***	0.0959	0.1229	-0.3809
			(0.0324)	(0.0851)	(0.1478)	(0.4875)
Relatedness^2					-0.2680+	0.4770
					(0.1396)	(0.5122)
Relatedness * Log(Experience)				-0.0341**		0.0749
				(0.0105)		(0.0639)
Relatedness^2 * Log(Experience)						-0.1034
						(0.0664)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	998,258	998,258	998,258	998,258	998,258	998,258
R-square (within)	0.1749	0.1750	0.1764	0.1766	0.1765	0.1766
R-square (overall)	0.2465	0.2464	0.2470	0.2468	0.2467	0.2461

1. Numbers in parentheses are robust and cluster standard errors.
2. + p<0.1; * p<0.05; ** p<0.01; *** p<0.001
3. Coefficients for dummy control variables, line, value, and agent workload are unreported.

The marginal effect for *Log (experience)* is -0.0020 and is not significant at the 0.05 level. Thus, H1 is not supported for the likelihood of inspection. This result suggests that experience itself may not help to improve the quality of customs agents' declaration processing. The marginal effect for *Relatedness* is negative and significant (β = -0.1869, p < 0.001), which suggests that higher relatedness of experience is associated with less inspection. Quantitatively, one standard deviation increase of *Relatedness* will lead to a 2.03% reduction in the likelihood of inspection. Considering that the average inspection rate is around 12.9%, this is a very significant improvement in agents' performance. However, the quadratic relationship is not supported and no coefficient is significant at the 0.05 level, so our H2 is also not supported for the likelihood of inspection.

Next, we find that the coefficient of *Relatedness * Log(Experience)* is negative and significant (β = -0.0341, $p < 0.01$). We again examine the impact of *Relatedness* under a low level of experience and a high level of experience. When experience is low (two standard deviations below the mean), the coefficient on *Relatedness* is -0.0883; when experience is high (two standard deviations above the mean), the coefficient becomes -0.2855. This implies that under a higher level of experience, the impact of relatedness will be stronger. Thus, our H3 is supported for the likelihood of inspection.

2.5.2 Robustness Checks

We conducted several analyses to examine the robustness of our empirical results. Table 2.6 and Table 2.7 report the results.[17]

[17] Due to space limitations, we exclude coefficients for all control variables from the table. Results are available from the authors upon request.

One important issue is whether our specification of the *Relatedness* measure is robust. We re-estimate our models under different specifications of *Relatedness,* and the results are summarized in Table 2.6. In Columns 1 and 2, we do not adjust for the relatedness between tasks from different categories in the dimensions of regime, customs house, and client groups. In Columns 3-6, we change the functions to convert distances to relatedness. We uses *Relatedness = 1/(1+Distance)* in Columns 3 and 4, and *Relatedness* = $e^{-Distance}$ in Columns 5 and 6. Both have been adopted in the prior literature (Shepard, 1987; Strehl, 2003). In Columns 7 and 8, we use average relatedness across the four dimensions to create the overall relatedness. In Columns 9 and 10, we switch the sequence of step 2 and step 3 to construct an alternative relatedness measure. Overall, the results are qualitatively similar to the main results, and our findings are generally consistent.

Table 2.6: Alternative Specifications of *Relatedness*

Model: DV	(1) No adjustment: Time to Complete	(2) No adjustment: Likelihood of Inspection	(3) 1/(1 + *Distance*): Time to Complete	(4) 1/(1 + *Distance*): Likelihood of Inspection	(5) $e^{-Distance}$: Time to Complete	(6) $e^{-Distance}$: Likelihood of Inspection	(7) Linear average: Time to Complete	(8) Linear average: Likelihood of Inspection	(9) Switching Sequence: Time to Complete	(10) Switching Sequence: Likelihood of Inspection
Log(Experience)	-0.0273 (0.0456)	0.0087^{+} (0.0046)	0.0004 (0.0495)	0.0241*** (0.0067)	-0.0058 (0.0489)	0.0176** (0.0060)	0.0865 (0.0536)	0.0099 (0.0072)	-0.0129 (0.0458)	0.0136** (0.0052)
Relatedness	1.5668* (0.7327)	0.0342 (0.0693)	1.8155* (0.7064)	0.1369 (0.0913)	1.5167* (0.7445)	0.0953 (0.0858)	3.1158*** (0.6273)	-0.0398 (0.0858)	1.5958* (0.7738)	0.0710 (0.0829)
Relatedness^2	-2.3416** (0.8659)		-2.2957** (0.8076)		-2.1516* (0.8499)		-3.6405*** (0.6988)		-2.4869** (0.8995)	
Relatedness * Log(Experience)	-0.2961** (0.0959)	-0.0225* (0.0094)	-0.3793*** (0.1025)	-0.0460*** (0.0117)	-0.3672*** (0.1041)	-0.0358** (0.0108)	-0.7342*** (0.1091)	-0.0164** (0.0054)	-0.3779*** (0.1038)	-0.0294** (0.0098)
Relatedness^2 * Log(Experience)	0.3951*** (0.1115)		0.4348*** (0.1131)		0.4365*** (0.1168)		0.7172*** (0.1087)		0.4854*** (0.1224)	
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	998,258	998,258	998,258	998,258	998,258	998,258	998,258	998,258	998,258	998,258
R-square (within)	0.0789	0.1761	0.0790	0.1772	0.0790	0.1767	0.0794	0.1759	0.0792	0.1763
R-square (overall)	0.0778	0.2463	0.0798	0.2466	0.0791	0.2466	0.0810	0.2465	0.0788	0.2464

1. Numbers in parentheses are robust and cluster standard errors.
2. $^{+}$ p<0.1; * p<0.05; ** p<0.01; *** p<0.001
3. Coefficients for all control variables are unreported.

Another concern is that the two dependent variables *TimeComplete* and *Inspection* can be correlated with each other. The most common approach to address this issue is to treat the two regress equations as a system and conduct seemingly unrelated regressions. We manually remove the fixed effects and re-run the analysis using seemingly unrelated regression (SUR) estimates. The results are reported in Columns 1 and 2 in Table 2.7. The results are very close to the main estimation results, and our findings are generally consistent.

Further, one common issue in the learning literature is the debate between cumulative output and calendar time as measures of experience (Argote, 1999). Researchers are often concerned that as experience increases with time, the learning curve analysis may only reflect a time trend rather than the effects of learning-by-doing. Following the prior literature (e.g. Reagans et al., 2005), we created a variable DaysElapsed to measure the calendar time a customs agent has performed customs declarations via the system. It is not surprising that the correlations between experience and calendar day are high. Columns 3 and 4 in Table 2.7 show the results of regressions in which we include both the experience variable and the calendar time variable. The coefficients of the independent variables are very close to the main results, and the calendar time variable is not significant. Thus, under our setting, the effect of experience is not just a reflection of the passage of time. We also run regressions to test whether the learning curve follows a log-linear relationship or log-log relationship. Columns 5 and 6 in Table 2.7 report the results, which are generally consistent.

Finally, as our data are longitudinal, we replicate our analysis using panel-specific heteroskedastic and AR(1)/PSAR(1) structures for the error terms of the regression model. Results are consistent with the main estimation (Columns 7-10 in Table 2.7). The level of serial correlation is low (AR(1) coefficient is 0.0013 for time to complete and 0.0002 for the likelihood of inspection), and it does not change the conclusions drawn from the coefficients.

Table 2.7: Robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Model: DV	SUR analysis: Time to Complete	SUR analysis: Likelihood of Inspection	Days Elapsed: Time to Complete	Days Elapsed: Likelihood of Inspection	Linear model for experience: Time to Complete	Linear model for experience: Likelihood of Inspection	AR(1): Time to Complete	AR(1): Likelihood of Inspection	PSAR(1): Time to Complete	PSAR(1): Likelihood of Inspection
Experience	-0.0055 (0.0088)	0.0169*** (0.0012)	-0.0053 (0.0472)	0.0165** (0.0062)	3.14e-06 (7.63e-06)	1.05e-06^{+} (6.10e-07)	-0.0182* (0.0082)	0.0077*** (0.0010)	-0.0172* (0.0081)	0.0077*** (0.0010)
Relatedness	1.4063*** (0.2561)	0.0954*** (0.0173)	1.4173^{+} (0.7399)	0.0960 (0.0852)	-1.5299*** (0.3996)	-0.1693*** (0.0337)	1.1023*** (0.2385)	0.0260^{+} (0.0142)	1.1362*** (0.2363)	0.0259^{+} (0.0142)
Relatedness^2	-2.0586*** (0.2241)		-2.0764* (0.8375)		1.4661*** (0.3391)		-1.7089*** (0.2104)		-1.7365*** (0.2088)	
Relatedness * Experience	-0.3710*** (0.0308)	-0.0341*** (0.0021)	-0.3722*** (0.1026)	-0.0342** (0.0105)	-2.93e-05^{+} (1.54e-05)	-1.85e-06** (6.05e-07)	-0.3062*** (0.0287)	-0.0188*** (0.0018)	-0.3099*** (0.0285)	-0.0188*** (0.0018)
Relatedness^2 * Experience	0.4391*** (0.0274)		0.4414*** (0.1150)		3.26e-05* (1.34e-05)		0.3746*** (0.0257)		0.3776*** (0.0256)	
Days Elapsed			-2.70e-06 (2.42e-06)	2.09e-06 (5.22e-06)						
Fixed effects	Wiped out	Wiped out	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	998,258	998,258	998,258	998,258	998,258	998,258	998,258	998,258	998,258	998,258

1. Numbers in parentheses are standard errors. Columns (3)-(6) use robust and cluster standard errors and Columns (1)-(2) and (7)-(10) use the ordinary standard errors.
2. In Columns (1)-(4) and Columns (7)-(10), we use the log-transformed values of experience in the estimation. In Columns (5)-(6), we use the original value of experience.
3. $^{+}$ p<0.1; * p<0.05; ** p<0.01; *** p<0.001
4. Coefficients for all control variables are unreported.

2.6 Discussion and Conclusion

2.6.1 Discussion of Results

Our study has several key findings. Our empirical results suggest that while the level of experience and the relatedness of experience can both affect workers' performance, they may have different impacts on different performance measures, such as task completion time versus quality. Our findings demonstrate that an increase in customs agents' levels of prior experience is associated with a reduction in their time to process a customs declaration. Further, the experience relatedness of the customs agents follows a U-shape relationship with the completion time. Both results are consistent with our research hypotheses. On the other hand, an increase in customs agents' experience is not linked with a significant reduction of the likelihood of inspection, and experience relatedness exhibits a linear relationship with the likelihood of inspection. Figures 2.6 summarizes the results. As shown in the figure, the customs agents' learning curve on the likelihood of inspection is much flatter than their learning curve on the completion time. Further, while the likelihood of inspection steadily decreases with increasing level of customs agents' experience relatedness, completion time first decreases with experience relatedness, but then increases with it.

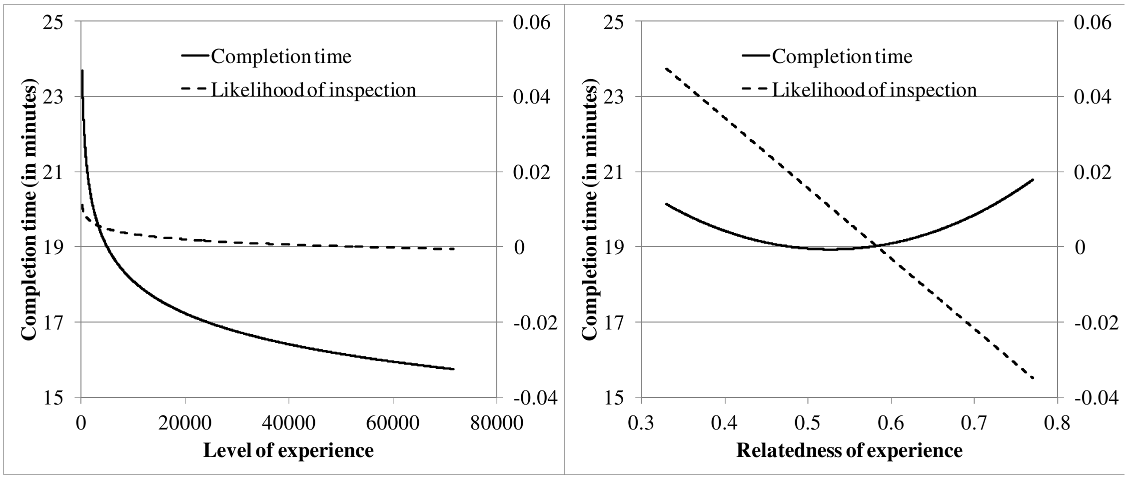

Figure 2.6: Level of Experience, Relatedness of Experience, and Performance

One possible explanation for the different results on the likelihood of inspection could be that customs agents need more skills to achieve higher declaration processing quality and avoid inspection, but they may only need a higher level of motivation to complete the declaration processing faster. In our context, the declaration processing task includes completing the primary declaration form, completing other forms required, submitting approval requests, and uploading attachments. Although there are variations in the details, the steps are quite standard and easy to learn. However, to select the most appropriate information to complete the forms (e.g., the tariff code for the goods) and to avoid mistakes, the customs agents need to understand the customs policies, the declaration itself, and the details of the merchandise. This is much more complex and more difficult to learn. Hence, only accumulating a greater level of experience that may not be highly related to the current task may not improve the quality of customs agents' work. Moreover, the literature also suggests that as task difficulty increases, the relative impact of skill on performance increases, and the relative impact of motivation on performance decreases (Bonner 1991, 1994; Campbell and Gingrich, 1986). In addition, prior research demonstrates that ability and skills can predict more on performance of difficult tasks than simple tasks (Chen, Casper, and Cortina, 2001; Schmidt and Hunter, 1998). Thus, the impact of customs agents' experience relatedness on their time to complete the declaration processing will be more transferred through its impact on motivation, and exhibits the U-shape; in contrast, the impact of experience relatedness on declaration processing quality will be more transmitted via its impact on skill, hence it follows the linear relationship.

In addition, we observe that the impact of experience relatedness on performance also differs under different levels of experience. Figure 2.7 depicts the impact of customs agents' experience relatedness on their time to complete the data entry task and probability of inspection for agents with low experience (two standard deviations below the average), average experience, and high experience (two standard deviations above the average). From the left panel of figure 2.7, we see that customs agents with low experience exhibit a shallower U-shape and customs agents with high experience show a steeper U-shape. For agents with low experience, average experience, and high experience, their times to complete declaration processing reach the minimum at a relatedness level of 0.965, 0.527, and 0.480, respectively. When workers' experience relatedness increases or decreases by one standard deviation from that minimum point (about 0.11), their time to complete the task will increase by 0.34% for low-experience agents, 1.89% for average-experience agents, and 3.44% for high-experience agents (about 4.9 seconds, 21.5 seconds, and 30.9 seconds, respectively). The right panel of figure 2.7 also suggests that the impact of experience relatedness is stronger for customs agents with higher experience. For one standard deviation change in experience relatedness, the probability of inspection will drop by 0.96% for agents with low experience, but will drop by 3.11% for agents with high experience. Summarizing the observations, we find that the impact of experience relatedness is greater under higher levels of experience for both time to complete the task and task quality.

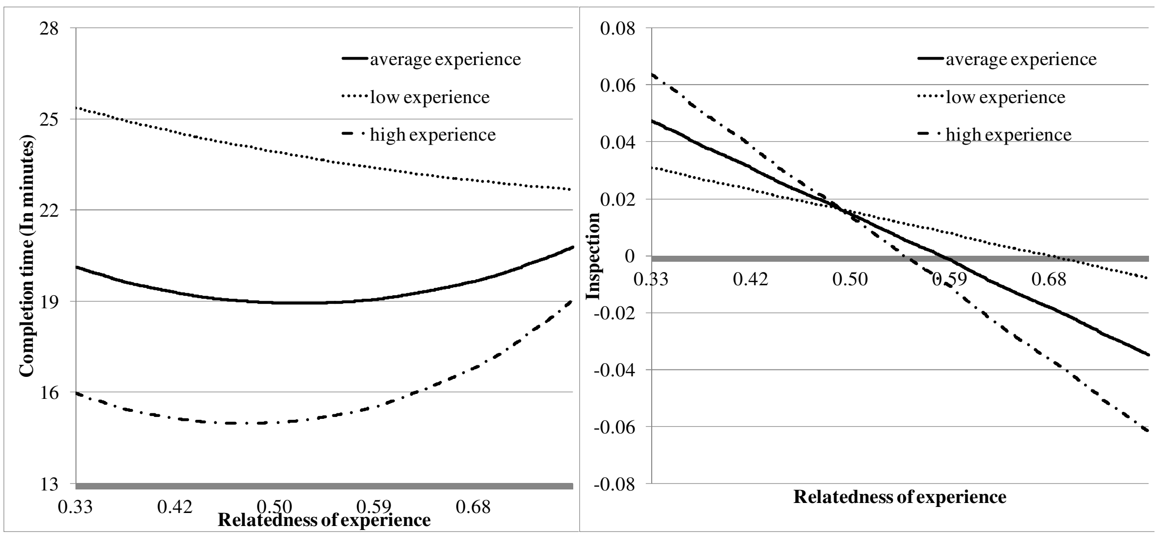

Figure 2.7: Experience Relatedness and Workers' Performance under Different Levels of Experience

2.6.2 Implications, Limitations, and Directions for Future Research

Our research has several theoretical contributions. First, our study contributes to the learning curve literature by conceptualizing and evaluating the role of experience relatedness on workers' performance in a more precise way. Unlike prior literature which simply classified experience into focal and related experience (e.g., Boh et al., 2007; Staats and Gino, 2012), we construct a continuous measure to assess the current task's degree of relatedness to workers' prior experience. By using this more discriminating measure, we attempt to respond to the call of nuanced investigation of the learning curves (Argote and

Miron-Spektor, 2011; Staats and Gino, 2012). We find that workers' experience relatedness has a significant impact on both their time to complete a task and the quality of their tasks. We argue that the relatedness of experience is likely to influence the magnitude of workers' skills applicable to the current task, as well as the workers' motivation and involvement in the current task. As both skills and motivation can affect the workers' performance (Staw, 1980), the overall impact of experience relatedness may be very complex. When we follow the traditional approach to construct focal and related experience variables under our setting, the amount of focal experience is relatively small.[18] Further, we can only observe a linear relationship for the relatedness of experience: related experience is associated with a larger improvement in completion time, while focal experience is associated with a larger improvement in completion quality.[19] This may lead to inappropriate conclusions for completion time, because it may also decline when experience is too much unrelated.

Second, we further demonstrate that the role of experience relatedness on workers' performance may be different for different performance measures, thus providing a better understanding of workers' task performance. Prior literature tends to focus on the investigation of a single performance measure, such as completion time (e.g., Clark et al., 2012; Staats and Gino, 2012) or quality (e.g., Clark and Huckman, 2012; KC and Staats, 2012; Levin, 2000). However, performance is a multidimensional construct and can be measured in different ways. In this study, we attempt to compare two related but distinct performance measures: completion time and completion quality. As different performance

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[18] Under this specification, the mean focal experience for a customs agent is 118.76, and the mean related experience is 9148.54. The mean values after log-transformation are 1.60 and 8.28, respectively.
[19] A summary of the results is included in Appendix B, as well as a comparison with our results.

measures may be influenced differently by workers' skills and motivation, the impact of experience relatedness could also be different. Our results suggest that for less skill-dependent performance measures such as completion time, the impact of experience relatedness follows an inverted-U shape. However, for more skill-dependent performance measures such as quality, the relationship may be linear. Our findings highlight that to understand the impact of experience relatedness on workers' performance, we not only need to understand the relatedness concept, but also have to understand the factors influencing the performance measures, because those factors can potentially influence the relationship between relatedness and performance.

Third, we show that the impact of experience relatedness is also different under different experience levels of the workers. Prior literature suggests that the role of experience relatedness depends heavily on the temporal dimension (Staats and Gino, 2012). In this study, we find that the impact of relatedness is greater when workers accumulate more experience. Its U-shape relationship with time to complete the task and linear relationship with task quality are both steeper under a higher level of experience. As a result, when workers accumulate more experience, the role of experience relatedness becomes more important, and task allocation becomes more vital to workers' performance. This finding can provide insights into the mechanisms by which relatedness affects workers' performance.

Our study also has methodological contributions. In the learning curve literature, the examination of relatedness is accomplished by decomposing experience into focal and related experience. However, this approach is overly simplistic when the experience can be decomposed into multiple facets (usually more than 2), as the decomposition will create too many distinct experience categories. Simply decomposing experience into multiple categories can also create problems for estimation of research models and interpretation of results when researchers want to understand the impact of all those experience categories. We provide a solution to this problem by constructing this distance-based continuous relatedness index, and this approach can be generalized to many different settings when the task is complex and can be characterized by multiple dimensions.

Our study can provide some insights for work assignments under different performance evaluation systems. Our results suggest a moderate level of experience relatedness is better for completion time, and a high level of experience relatedness is better for quality. Thus, when the first priority in performance is completion time, it is better to assign a balanced portfolio of tasks to the workers. On the other hand, when quality is more important, keeping a specialized and focused task portfolio would be superior. Such tailored work assignment can potentially improve the workers' operational performance.

Although our findings are robust to different specifications, our study is not without limitations. First, we focus on the examination of one particular research setting: the customs processing service in one country. While this focus helps to control mathematically for factors that would otherwise need to be incorporated in the analysis, it would be helpful for further studies to investigate other settings. Second, while we consider two important performance measures for the customs work, there may also be other possible measures of performance. Future research can attempt to explore the impact of relatedness on other performance indicators as well, because they may rely on different combinations of workers' skills and motivation. Third, while we use agent-fixed effects to control for the impact of customs agents' ability and personal traits on their performance, it may be interesting to further examine how other worker characteristics influence their learning curves and the impact of experience relatedness. Finally, while the agents are the most important persons in the task, the firms they are working with can also alter their learning curve. For example, agents who work independently or in small firms may only rely on their own experience, but agents in large firms can enjoy many supporting services, such as training and some documentation works of copying and scanning. An area for future study would be to investigate how organizational contexts affect the individual workers' learning curve, as well as the role of experience relatedness.

CHAPTER 3

LEARNING-BY-WORKING-TOGETHER IN COOPERATIVE SERVICE TASKS: THE MODERATING ROLE OF TASK COMPLEXITY AND TASK-LEVEL GOAL CONFLICT

3.1 Introduction

Learning-by-doing refers to the capability of workers to improve their task performance through their experience on the tasks (Arrow, 1962). While many studies have documented the benefits of such learning-by-doing in various manufacturing industries (e.g., Argote, 1999; Dutton and Thomas, 1984), only a few recent studies have investigated this effect under the service setting (e.g., Boh, Slaughter, and Espinosa, 2007; Boone, Ganeshan, and Hicks, 2008; Pisano, Bohmer, and Edmondson, 2001; Reagans, Argote, and Brooks, 2005; Wiersma, 2007). Given the growing importance of service work in the world economy, there is a strong need to understand how service workers' experience helps them to improve their performance. In particular, service tasks are often characterized as highly variable, non-repetitive, and highly customized (Boone et al., 2008). Therefore, learning and accumulating knowledge are especially important in the service industries. However, knowledge is less codified in service tasks, so it is harder for the service workers to learn to perform their tasks simply from textbooks or manuals. Under this circumstance, service workers' experience on the tasks becomes an importance source of their learning.

Further, in many service settings, the tasks need to be completed by a dyad of individuals (e.g., a service worker and a client). Due to the interdependent nature of the task, the individuals in the dyad have to cooperate with each other, and the service output will be "co-produced" rather than being completed by one individual worker (Larsson and

Bowen, 1989). This co-production of service may imply a bilateral learning in the dyad. Both individuals in the dyad have to learn to perform the task, and they also need to learn to work with each other. In this study, we focus on the latter learning effect by investigating the relationship between a dyad's experience working together and its task performance. We label this potential effect as an effect of *learning-by-working-together*. Such learning effect may be of specific importance for the service tasks completed by dyads, as the individuals in the dyads can have different kinds of conflicts with their counterparts. For example, in customs inspections, travelers and government officials can have conflicting goals. Travelers may wish to minimize the customs duty, while the government officials want to ensure the appropriate duty collection. Further, the two parties may hold different views towards the same commodity, which can also increase the goal conflict. We argue that through repeated interactions with each other, the dyad can develop a mutual understanding with each other, achieve better information sharing, and establish a relationship with trust (Boone et al., 2008; Clark, Huckman, and Staats, 2012; Elfenbein and Zenger, 2013; Jehn and Shah, 1997; McEvily, Perrone, and Zaheer, 2003). Those factors may help the dyad to resolve the conflicts and improve the dyad's task performance. Thus, our first research question is: is an increase in a dyad's experience working together associated with an improvement in their task performance?

In addition to examining the overall effect of the dyad's learning-by-working-together, we also seek to study how this effect varies for different tasks. In particular, we examine two important task characteristics that may moderate the relationship between a dyad's experience working together and their task performance. The first factor we consider is the task complexity, which is often considered as an important driver of task performance. Drawing literature on information processing and cognitive load theory (Kirschner, Paas, and Kirschner, 2009; Kirschner, Paas, and Kirschner, 2011), we argue that cooperation within the dyad can help them to address the task complexity. When the individuals in the dyad have more experience working together, they can achieve more effective and efficient cooperation with each other, which may be more beneficial for complex tasks. Another factor we study is the level of goal conflict embedded in the task. We propose that high level of goal conflict in the task hinders the dyad's motivation for cooperation before they start to work together (Locke and Latham, 1990; Locke, Smith, Erez, Chah, and Schaffer, 1994), thus reduces the impact of dyad experience on dyad performance. We also argue that the two task characteristics may have a joint effect on the dyad's learning-by-working-together, because the resolution of task complexity or goal conflict within the dyad may reinforce the resolution of the other (De Dreu, 2006; De Dreu and West, 2001; Jehn, 1995). Thus, we ask the following three research questions: First, how does the impact of a dyad's experience working together on their task performance vary for tasks with different levels of complexity? Second, how does the impact of a dyad's experience working together on their task performance vary for tasks with different levels of goal conflict? Third, how does the impact of a dyad's experience working together on their task performance vary for tasks with different combinations of complexity and goal conflict?

To answer those questions, we study a particular service task completed by dyads: customs inspections in Costa Rica. Customs are getting a growing attention because of the increasing level of globalization and international trade. According to the WTO (2012a), the total values of merchandize and commercial service exports was estimated at US$

20.87 trillion, which constituted almost 30% of the world GDP. As an important transaction hub in the Central America region, Costa Rica also relies heavily on its international trade. In 2011, the country ranked 2nd in the values of both import and export trade in this region (WTO 2012b), and also collected 5% of its revenue from international trade taxes (World Bank, 2012). Therefore, a thorough understanding of customs inspection tasks may bring extensive benefits to the Costa Rican economy.

Our setting offers a unique opportunity to under the learning-by-working-together effect in service tasks and the moderating role of task characteristics. First, in Costa Rica, the customs inspection process requires the cooperation of two groups of individuals – customs agents and customs inspectors. Customs agents are third party individuals employed by the importers and exporters to clear the goods through the customs, and customs inspectors are government officials to check the goods. During the inspection, the agent and the inspector must meet and communicate with each other to figure out the appropriate customs duty amount for the goods. They also exhibit natural conflicts in their goals: the agent may wish to minimize the duty payment, whereas the inspector wants to maximize it. Thus, under this setting, the agent-inspector dyad's learning from their experience working together may be quite salient. In addition, customs inspections may vary in their levels of complexity, such as the amount of goods involved. Meanwhile, the inspections can also differ in their magnitude of goal conflict, as different inspections may contain different types of goods that are subject to different duty rates, thus lead to differences in potential goal conflicts between the agent and the inspector. As a result, this setting allows us to evaluate the impact of an agent-inspector dyad's learning-by-working-together on their performance in tasks with different levels of complexity and goal conflict.

We adopt the traditional learning curve model with dyad fixed effects to evaluate the performance implications of the agent-inspector dyad's experience working together. In particular, we examine how the dyad's experience working together influences their time to complete the inspection. We collected detailed data on customs inspections conducted in Costa Rica between July 2005 and May 2011. Our data includes 323,520 customs inspections completed by 19,311 agent-inspector dyads during that period. In our analysis, we also control for the impact of the individual agents and inspectors' experience outside the focal dyad and other declaration-specific characteristics on the dyad's performance. There are four key sets of results. First, we show that an increase in an agent-inspector dyad's experience working together is associated with a decrease in the time of completing an inspection task for the dyad. Second, we demonstrate that the impact of dyad experience on dyad performance varies for customs inspections with different levels of complexity and goal conflict. Our results suggest that dyad experience has a larger effect on the performance of high-complexity tasks than low-complexity tasks. On the other hand, dyad experience exhibits a weaker effect on the performance of high-conflict tasks than low-conflict task. Third, we find that task complexity and task-level goal conflict also have a joint effect on the relationship between dyad experience and dyad performance. When the customs inspection is complex and involves high level of goal conflict, the impact of dyad experience is the greatest. We discuss the implications of our results and also conduct several robustness checks to evaluate the consistency of our results.

This study contributes to the literature from several aspects. We contribute to the literature on learning curves in service tasks by demonstrating the existence of learning-by-working-together effect for tasks completed by dyads with conflicts. We argue that improving experience working together may mitigate the effect of conflicts within the dyads. We also see that the impact of experience can vary across tasks with different characteristics. This may provide additional insights into the underlying mechanisms by which experience improves task performance. Finally, our findings can also have implications on task assignments for similar service work completed by dyads.

3.2 Theory and Hypotheses Development

3.2.1 Dyads' Experience Working Together and Their Task Performance

In some service settings, tasks are usually completed by dyads such as a worker and her client rather than an individual worker. Because of the interdependence nature of the service, the dyad must interact to "co-produce" the service output (Larsson and Bowen, 1989). For example, the architecture engineer needs to work closely with her clients during their provision of the architecture design services (Boone et al., 2008). Similarly, in customs services, the customs inspectors must also cooperate with the customs agents to complete the inspection task. Under such settings, the actions of both parties in the dyad will contribute to the successful completion of the service task.

Prior literature argues that one primary concern in tasks completed by dyads is the conflict between the individuals in the dyad (De Dreu and Weingart, 2003). One type of conflict that usually occurs within the dyad is the goal conflict, which refers to the existence of inconsistent preferred outcomes or end-states (Rahim, 1992). For example, in the customs inspection tasks, the customs agents usually wish to minimize the customs duty payment, while the customs inspectors have a conflicting goal: maximizing the duty amount. This kind of conflict is usually associated with a reduction of task performance (Cosier and Rose, 1977).

When the individuals in the dyad work together, they can also have other types of conflicts, such as task conflict and relationship conflict. Task conflict is a perception of disagreements among the individuals regarding the task, which involves differences in the viewpoints and mindsets of those individuals (Jehn, 1995). During the customs inspections process, customs agents may hold different opinions with the customs inspectors towards the same goods. For example, the agents may perceive a GPS device installed on a car as electrical equipment, while the inspectors will classify it as car accessories. On the other hand, relationship conflict refers to the perception of interpersonal compatibility within the dyad, such as tension, annoyance, and animosity (Jehn, 1995; Simons and Peterson, 2000). A customs inspector's personal dislike towards a certain customs agent is a good example of relationship conflict in the customs inspection tasks. The conflict literature suggests that relationship conflict has a detrimental effect on task performance (De Dreu and Weingart, 2003; de Wit, Greer, and Jehn, 2012). Further, while studies show mixed results on the direct relationship between task conflict and performance (de Wit et al., 2012), researchers also demonstrate that task conflict can have an indirectly negative effect on task performance by increasing relationship conflict (Curşeu and Schruijer, 2010; Simons and Peterson, 2000).

We argue that increase in a dyad' experience working together can help to resolve the above kinds of conflicts in the dyad and improve their task performance for several reasons. First, through repeated interactions with each other, the dyad can develop a better understanding of each other; this may allow for more efficient execution of work (Boone et al., 2008). Especially, the dyad can build up a common language or a universal mindset through their experience working together, such that they can better communicate with each other (Weber and Camerer, 2003). This mutual understanding and universal mindset can reduce the possibility of task conflict (Jehn et al, 1997), and also can improve the efficiency in resolving the task conflict (Brehmer, 1976), thus improving the dyad's task performance. In addition, when individuals in the dyad understand each other better, they may also have a better knowledge of each other's goals, which reduces their goal conflict. For example, when a customs agent and a customs inspector work together more, they will have a better perception of how each other classifies different types of goods, and they are also more likely to establish a shared classification schema. This schema can further facilitate the agent and the inspector's agreement on the appropriate duty amount to pay, and they will have less conflict in that. Second, repeated interactions within the dyad can facilitate the information sharing with each other (Clark et al., 2012; Jehn and Shah, 1997). More interactions imply that the individuals in the dyad know each other better and may be more willing to share information with each other, which can also reduce the level of task conflict as well as relationship conflict (Moye and Langfred, 2004). Third, when the dyad interacts more with each other, they may establish relationship and trust with each other (Adler, 2001; Elfenbein and Zenger, 2013; Lubatkin, Florin, and Lane, 2001; McEvily, Perrone, and Zaheer, 2003). The inter-dyad trust can also reduce task conflict and relationship conflict within the dyad (Curşeu and Schruijer, 2010; Peterson and Behfar, 2003; Simons and Peterson, 2000). A customs inspector can learn the trustworthiness of a customs agent from her experience working with the agent, and her trust in turn will reduce the misunderstanding and tension when they work together on customs inspections. Overall, we expect that through reducing different types of conflicts with in a dyad and improving the efficiency in resolving the conflicts, the dyad's experience working together can improve the effectiveness and efficiency of their cooperation, as well as the task performance for the dyad. Thus, we hypothesize:

H1: An increase in the dyads' experience working together has a positive impact on their task efficiency.

3.2.2 Task Complexity, Task-level Goal Conflict, and the Impact of Dyad Experience

Task complexity is an important driver of task performance. It is usually associated with the amount of information load, the level of information diversity, and the rate of information change for the task (Campbell, 1988; Schroder, Driver, and Streufert, 1967). As task complexity increases, the cognitive load or cognitive demand associated with the task also increases (Campbell and Gingrich, 1986). When the cognitive load goes beyond the cognitive capacity of the individuals performing the task, the task performance will start to deteriorate (Schroder et al., 1967).

For tasks performed by a dyad, cooperation within the dyad can mitigate the impact of the substantial cognitive load imposed by high-complexity tasks. The dyad can divide the cognitive load for the individuals, thus reducing the risk that the individuals have to process more information than their cognitive capacity (Hinsz, Tindale, and Vollrath, 1997; Kirschner et al., 2011; Ohtsubo, 2005). While the division of cognitive load also requires the dyad's cognitive effect to communicate with each other and coordinate their actions (Kirschner et al., 2009; Yamane, 1996), this cost tends to be overweighed by the benefits for high-complexity tasks. For low-complexity tasks, the division of cognitive load may be less beneficial, because the individuals have sufficient capacity to cope with the information load (Kirschner et al., 2011).

According to H1, when the individuals in the dyad have more experience working together, they can achieve more effective and efficient cooperation with each other. Through mutual understanding, information sharing, and trust building, the dyad's experience working together can reduce their effort for communication of information and coordination of actions. Thus, we also expect that the dyad's experience working together is more beneficial for more complex tasks. For instance, the inspection of a very complex customs declaration may require heavy communication between the agent and the inspector to divide the work. When they work with each other more, they are more likely to develop an effective mechanism for such communication, which in turn improves their performance. On the other hand, the communication need for inspecting a simple customs declaration may be very low, and the increase in the dyad's experience working with each other will be less beneficial. As a result, we offer the following hypothesis:

H2: The impact of dyads' experience working together on their task efficiency will be greater for complex tasks than for simple tasks.

In H1, we expect that a dyad's experience working together can reduce goal conflict within the dyad and improve their task performance. However, it is also possible that the level of goal conflict embedded in the task will affect the effectiveness of dyad experience. For example, in tax auditing, high-income taxpayers usually have more goal conflict with the tax auditor than low-income taxpayers, as high-income taxpayers are more willing to minimize their tax payment. Similarly, the inspection of a customs declaration with high-duty goods may imply a higher level of goal conflict between the customs agent and the customs inspector for this task, because the customs agent will have more incentives to minimize the duty payment, and the customs inspector will exhibit more incentives to maximize it. This difference in the task-level goal conflict across different customs inspection tasks can bring to significant variation in the impact of dyad experience.

Prior literature argues that high level of goal conflict hinders the motivation of cooperation, because it is less likely for the individuals to achieve their own goals (Locke and Latham, 1990; Locke et al., 1994). For instance, when a customs declaration involves high-duty goods such as cars, the customs agent may adopt a less cooperative behavior (e.g., more arguing towards a lower duty payment), even though she may have many interactions with the customs inspector. On the other hand, the inspector can also be pickier and less cooperative with the agent, because the inspection of this declaration becomes very important for the inspector. Further, task-level goal conflict can also affect the effectiveness of coordination strategies within the dyad. In general, individuals working together can adopt two types of coordination strategies: organic and mechanistic (Burns and Stalker, 1961). The organic approach is more informal, cooperative, and decentralized, while a mechanistic approach is perceived as more formal, controlling, and centralized. While individuals in a dyad work together more, they can develop an organic coordination strategy by achieving a mutual understanding with each other and facilitating information sharing. However, this strategy will be less effective when the level of goal conflict is high for the task, because the individuals in the dyad will be reluctant to cooperate, and they are less likely to utilize their mutual understanding and sharing information with each other (Andres and Zmud, 2002). For example, the customs agent may share less information with the customs inspector about the customs declaration when it contains goods that are subject to higher duty rates. Overall, we propose:

H3: The impact of dyads' experience working together on their task efficiency will be weaker for tasks with higher levels of goal conflict than for tasks with lower levels of goal *conflict.*

While task complexity and task-level goal conflict exhibit separate moderation effects on the relationship between dyad experience and dyad performance, those factors can also have a joint moderation effect on this relationship. As the complexity of the task increases, the need for cooperation within the dyad also increases, because the cognitive load posed on the individuals in the dyad is likely to go beyond the individuals' cognitive capacity (Campbell and Gingrich, 2006). Therefore, we expect that for high-complexity tasks, the impact of high task-level goal conflict on the dyad's experience-performance relationship will be weaker, because the need for cooperation from high complexity offsets the reluctance to cooperate under high-conflict tasks. This effect will be lower for low-complexity tasks, because the cooperation need is not as urgent for those low-complexity tasks.

Further, when task complexity is higher, the individuals in the dyad need to communicate more with each other. The increase in communication helps to resolve the conflict, as argued in H1. On the other hand, during the conflict resolution process, the individuals in the dyad need to present their respective opinions, information, and knowledge to each other (Yan, 2011). This process allows the dyad to share their information more thoroughly, process the information at a deeper level, and consider more possibilities (De Dreu, 2006; De Dreu and West, 2001; Jehn, 1995). As a result, the dyad can better cope with high-complexity tasks. When the level of task complexity is extremely high, high task-level goal conflict may even improve the effectiveness of the dyad's experience working together. For example, during the inspection of a complex customs declaration, the customs agent and the customs inspector often communicate frequently to determine the best way to check the goods. Through communication, they can understand better the nature of the goods and resolve the potential conflict from those high-duty goods more efficiently. Meanwhile, through their discussion on the high-duty goods, the agent-inspector dyad can also develop better approaches to address the complexity in the customs inspection task. When the agent and the inspector work together more, they will have more efficient communication with each other, and the above mechanisms will be more effective in improving the agent-inspector dyad's task efficiency. To sum up, we hypothesize the following:

H4: The negative effect of task-level goal conflict on the relationship between dyads' experience working together and their task efficiency will be weaker for high-complexity tasks than for low-complexity tasks.

Figure 3.1 summarizes our research hypotheses. Our research model suggests that a dyad's experience working together is positively associated with the dyad's task performance, and the relationship is moderated by task complexity, task-level goal conflict, and the interaction of the two factors.

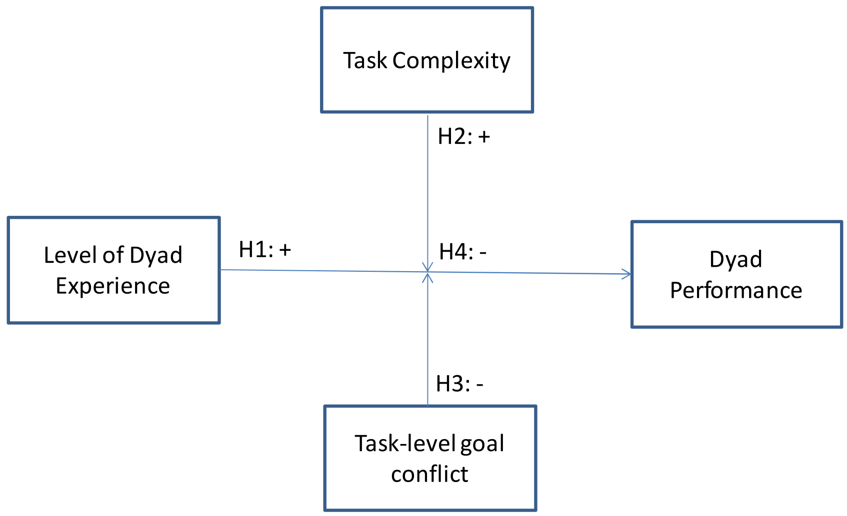

Figure 3.1: Overall Research Model

3.3 Research Setting

Our research setting is the customs inspection process in Costa Rica. In Costa Rica, the customs inspection process involves the cooperation of two types of workers – customs agents and customs inspectors. In this section, we will introduce the role of the customs, the customs agents and customs inspectors, and the general customs inspection procedure.

Customs in Costa Rica. Customs is an authority or agency in a country responsible for collecting and safeguarding customs duties and for controlling the flow of goods into and out of the country.[20] As the level of global trade has grown dramatically during the last decade, the customs has become a vital entity for the economy. According to WTO (2012a), in 2011, the total value of merchandise exports from its members reached US$ 16.7 trillion, and the total value of commercial service exports is estimated at US$ 4.17 trillion. Those numbers represent an annual increase of 10% since 2005. As a result, it is critical for

[20] http://en.wikipedia.org/wiki/Customs.

customs work to be performed correctly and efficiently.

As an important hub in the Central America region, the Costa Rican economy also relies heavily on its international trade. The values of imports and exports for Costa Rica in 2011 amounted to $16.22 billion and $10.41 billion US dollars, which both ranked 2nd after Panama in the Central America and Caribbean region (WTO, 2012b). Besides, Costa Rica has bilateral free trade agreements with more than ten countries and regions, including United States, China, Mexico, and European Union.[21] The country has established multiple customs houses to process trades from the land, the sea, and the air: two customs houses at the Nicaragua and Panama borders, one customs house at a major port on the Pacific Ocean, one customs house at a major port on the Caribbean Sea, one customs house at the main airport, and one central customs house. All houses have experienced a significant level of increase in the volume of transactions since 2005, with the only exception of year 2009 when the recession came.

Customs agents and customs inspectors. The customs inspection process involves the cooperation of two groups of workers: customs agents and customs inspectors. Customs agents are third party individuals who are employed by importers and exporters to clear the goods through the customs. Their major services include the preparation and submission of customs declarations to the customs. When the declarations require inspection, they also need to communicate with the customs inspectors to resolve the issues. As learned from our interviews, in Costa Rica, customs agents must hold the Licentiate degree to become

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[21] http://en.wikipedia.org/wiki/List_of_bilateral_free_trade_agreements. The trade agreement with European Union is not included in the list, but according to http://europa.eu/rapid/press-release_IP-12-1353_en.htm, the agreement was already approved by the European Parliament and will enter into force later in 2013.

eligible for work.

On the other hand, customs inspectors are government employees who conduct inspections of customs documents and physical goods. Their major responsibility is to figure out problems such as errors in tariff codes, and to ensure the collection of customs duties. Our interviews denote that the inspectors usually check the goods very carefully to make sure that all the information in the documents matches with the goods, including the quantities, the serial numbers, the tariff codes, and the monetary value. Besides, we also note from the interviews that the elder inspectors are usually less educated (e.g., only with high school degrees), but the younger inspectors should hold at least the same level of education as the customs agents. Further, they must also have two years of experience in the customs field before becoming a customs inspector.

The customs inspection process. In Costa Rica, the customs utilize a channel system (or more visually, a "light" system) to determine which customs declaration has to go through the inspection process. If the declaration is assigned with a "green light", the agent can pick up the goods immediately without any inspection. However, if the declaration is assigned with a "yellow light" or "red light", the declaration must be inspected. The assignment of the "light" is conducted by the customs automation system without any human intervention. Our interviews suggest that the assignment algorithm involves the examination of the electronic documents submitted by the agents, the judgment of potential risk, and some randomness.

When a declaration is selected to go through the inspection process, a customs inspector will be assigned. Our interviews indicate that the assignment is purely random; an agent may face 10 different inspectors in 10 inspected declarations. Sometimes (not too frequently), the inspector assigned may not be available, and a second inspector will be re-assigned. The system will inform the agent and the agent needs to call the inspector to set up a meeting arrangement for inspection of the documents and goods. According to the interviews, the arrangement is mostly settled in the same day, usually one or two hours after the red light is assigned. Once the meeting arrangement is settled, the agent must take all the original documents to see the inspector at the warehouse where the goods is stored. The inspectors will check the details of the original documents to validate the information submitted in the electronic documents. When the declaration is assigned a “red light”, the inspectors will also carefully verify the electronic documents, the original paper documents, and the physical goods match in all aspects, including the quantities, the serial numbers, the tariff codes, and the monetary value. This is to ensure that the customs duty is calculated and collected correctly. During the meeting, the agent and the inspector can also discuss to resolve issues emerged from the inspections. If all issues are resolved in the meeting, the inspector will give an approval to release the goods via the system using the computers installed in the warehouses, and the inspection process ends. Otherwise, the agent and the inspector must communicate via the customs automation system to resolve the remaining issues after the meeting, which may take from hours to days. The approval to release the goods cannot be given until all the issues in the declarations are fixed. If the declaration information recorded in the customs automation system (e.g., the correct tariff code or amount of customs duty) is not consistent with the correct information discovered in the inspection process, the inspector also has to revise the information before giving the approval. Figure 3.2 summarizes the process.

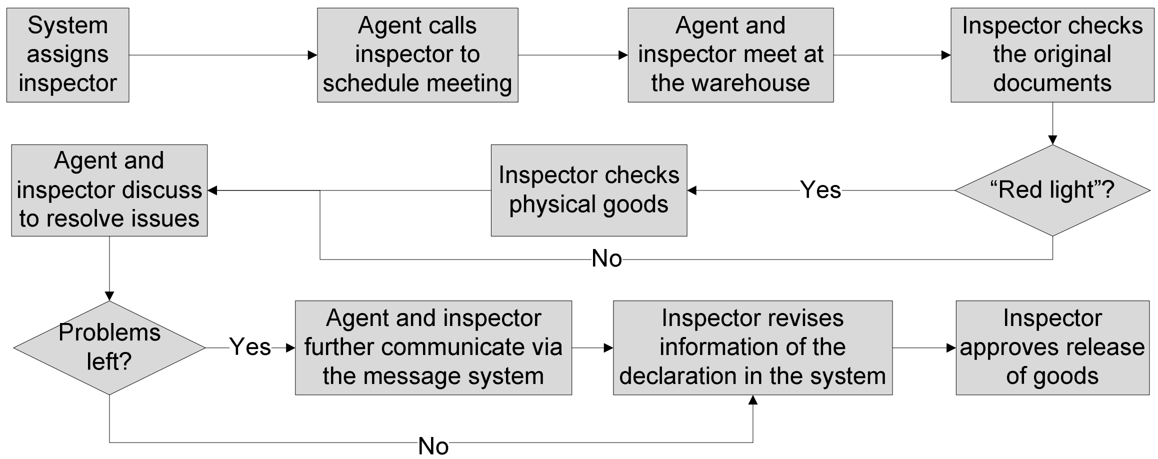

Figure 3.2: The Customs Inspection Process

During the customs inspection process, the agent and the inspector have to communicate often to complete the task. They may hold different opinions on the same merchandise and need to discuss to find out the most appropriate one. For example, for a flat-screen device, the customs agent may perceive it as a TV screen, but the customs inspector may think it is a computer monitor. As the duty rate will differ significantly between the two classifications, this can significantly influence the amount of communication within the agent-inspector dyad and the time to complete the inspection. As the agent and the inspector grow experience working together, they can have a better understanding of each other's view towards such classification and make agreements more quickly, and they can develop trust on the correctness of the declaration information submitted into the system. Those factors can potentially influence the agent-inspection dyad’s efficiency in the inspection of customs declarations.

Our setting offers several benefits for our investigation of the learning-by-working-together effect. First, under our setting, while the agents and inspectors must work together to complete the task, they have different goals. Our interviews suggest that the agents want to minimize the customs duty they need to pay, while the inspectors wish to maximize the duty payment. Thus, this setting allows us to investigate the impact of the agent-inspector dyads’ experience working together on their task efficiency under the existence of goal conflicts. In addition, the tasks processed by the agent-inspector dyad can vary significant in their details, including the complexity and the task-level goal conflict. This makes possible the investigation of how those task characteristics influence the impact of dyads’ experience working together.

Second, this setting also helps to control for several factors that may bias our results. One important issue is that the setting helps to eliminate the impact of the agent-inspector dyads’ experience working together before our data collection. Our data ranges from July 2005 to May 2011. While we do not observe the interactions between the agents and the inspectors before July 2005, we argue that it will not significantly affect our results. In 2005, the Costa Rican government implemented a customs automation system to improve the efficiency and the transparency of the customs process. Our interviews with the customs agents suggest that there were many underground activities undertaken before the implementation of the system, and usually the customs agents would pay the inspectors to get their goods through quickly. Under such circumstance, the agent-inspector relationship was not based on mutual understanding, information sharing, or trust, and their experience working together were also not associated with their relationship and task performance. When the customs automation system is implemented, everything became transparent and the underground activities were prohibited. Thus, the agents and inspectors had to re-develop their relationship under the new policies and regulations, and the old experience was mostly irrelevant. Besides, the government adopted a new approach to rotate the inspectors across different locations, so that the agents were less likely to work with inspectors they had experience with before the implementation of the system. This further reduces the level of the agent-inspector dyads' unobserved prior experience. Overall, the impact of unobserved prior dyad experience will be less of a concern under our setting.

Another important benefit of our setting is that it also controls for the communication within the dyad outside the tasks, which may significantly influence our results. Our interviews show that after the implementation of the customs automation system, the inspectors are only allowed to meet with the customs agents when they inspect the original paper documents and the physical goods, and other communications about the tasks must be conducted via the messaging functions in the customs automation system. Further, meetings between the agents and the inspectors outside the task are not allowed. As a result, the only way to develop mutual understanding, better information sharing, and trust within the agent-inspector dyads is through working together on the customs inspection tasks.

3.4 Data and Variables

3.4.1 Data

To test our research hypotheses, we collected detailed longitudinal data on the customs declarations going through inspections between July 2005 and May 2011 from the public website of the customs automation system. Our data contains the encrypted identifiers of the individual agents and inspectors processing the declaration, basic characteristics of the declaration such as customs house, channel, type of goods involved, monetary value of goods, customs duty amount, and different timestamps associated. The final sample contains 323,520 customs declarations processed by 19,311 agent-inspector dyads over the 6-year period.

In addition, we made three field visits to Costa Rica and conducted interviews with customs agents, importer firms, and the government officials. We also conducted several conference calls with one importer to complement the interviews and resolve problems that emerged in our study. The interviews and conference calls help us to better understand the customs inspection process, the work of customs agents and customs inspectors, and the policy of customs houses regarding inspection. The interview data is also used to interpret our results.

3.4.2 Dependent, Independent, and Control Variables

Dependent Variable. Our dependent variable is the time it takes to complete the inspection of a customs declaration for an agent-inspector dyad. Past studies examining learning in the service context have often relied on similar types of measures of time to complete the task (e.g., Clark et al., 2012; Mukhopadhyay et al., 2009; Pisano et al., 2001; Reagans et al., 2005). Following the literature, we define our dependent variable, *InspectionTime,* as the time spent between the channel assignment (start of the inspection process) and the final release of goods (end of the inspection process). Our interviews with several customs agents show that the importers and exporters want the goods to pass through the customs houses as quickly as possible, and they perceive the inspection time as an important factor to evaluate the customs agents' performance. In contrast, the Costa Rican government has regulations that limit the maximum time for an inspector to check the goods.[22] Further, the inspectors are facing an increasing level of inspections, which forces them to process the customs declarations in a timely manner.

Independent Variables. DyadExperience is our first major independent variable, which is measured as the cumulative number of inspected customs declarations processed by the same agent-inspector dyad prior to the current declaration. Our construction of the experience variable is similar to the cumulative output used in learning curve research on manufacturing and other industries (For example, Argote, 1999; Boh et al., 2007; Reagans et al., 2005). While our experience variable does not the capture the agent-inspector dyads' experience working together prior to our data collection, our setting helps to eliminate the impact. As learned from the interviews, the need for a relationship between the agents and the inspectors was very weak before the implementation of the customs automation system (i.e., the start of our data), and the agent-inspector dyads' experience working together has little impact on their performance. In addition, the rotation strategy of inspectors further destroyed the relationship, and every individual agent (inspector) had to work with an unknown inspector (agent) when the customs automation system was implemented. Hence, we are confident that our results will not be biased by our operationalization of dyad experience.

Our second independent variable *Line* measures the complexity of the customs

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[22] According to our interviews, the inspectors have to respond to the agents within 72 hours. However, each inspection may involve several rounds of communications, so the overall inspection process may span from days to weeks, or even months.

declaration processed by the agent-inspector dyad. It is defined as the number of lines of goods involved in the customs declaration. When the customs declaration involves more lines of goods, there will be more information on the goods to be processed by the dyad in the inspection process. As a result, the complexity to inspect the declaration will also increase (Schroder et al., 1967).

Our third independent variable *DutyRate* proxies for the level of goal conflict within the agent-inspector dyad on the current customs declaration. Our interviews demonstrate that the primary goal conflict in the customs inspection process is centered on the amount of the customs duty, whereas the customs agents seek to minimize the duty and the customs inspectors aim to maximize the duty. Hence, we expect that customs declarations with goods that are subject to higher duty will be associated with a higher level of goal conflict between the agent and the inspector. We calculate the variable by dividing the customs duty amount by the value of goods. This relative measure eliminates the impact of value of goods, because the value of goods is affected by the number of lines of goods, and will be highly correlated with our measure of complexity *Line*.

Control Variables. We consider a number of variables that may affect our dependent variable. One issue is that the individual agents and inspectors can also acquire knowledge about the customs inspection task when they work outside the dyad. To control for potential individual learning-by-doing effects, we create two variables measuring agents' and inspectors' prior individual experience processing inspected customs declarations outside the dyad working on the focal declaration. *AgentOtherExperience* is measured as the cumulative number of inspected customs declarations processed by the same agent but different inspectors in the past, and *InspectorOtherExperience* is measured as the cumulative number of inspected customs declarations processed by the same inspector but different agents.

Our interviews suggest that certain types of goods, such as automobiles, may require specific procedures and additional time to complete the inspection. To control for procedure and efficiency heterogeneity across different types of goods, we define a vector of 16 dummy variables *Sector*, indicating whether a specific sector of goods (for example, chemical products or automobiles) is included in the declaration. As we are able to observe the tariff codes of goods included in the declaration, we use the harmonized system codes to categorize the goods.

Similarly, we include a vector of 6 dummy variables *House* which represents the location where the declaration is submitted to. Our interviews show that in Costa Rica, each customs house has its own management. Thus, the customs inspection process and criteria can also vary across different customs houses, and *House* can help to control for this heterogeneity. We also include a dummy variable *Channel* to control for the efficiency difference between customs declarations going through "red light" and "yellow light".

To control for technological improvement of the system and other time-varying factors, *Month* is a vector of dummy variables indicating the calendar month when the declaration was entered. As our data ranges from July 2005 to May 2011, we include a total of 69 dummy variables and make July 2005 as the baseline.

Recent operational research indicates that workers' workload can significantly affect their service time (KC and Terwiesch, 2009; Staats and Gino, 2012). We also include several control variables to address this issue. First, we include two vectors of dummy variables *Dayofweek* and *Hour,* which indicate the day of week and hour when the customs inspection process started. They help to capture the workload and productivity differences across day of week and time of day.

Further, we create two continuous variables to measure the individual customs agent and customs inspector's workload during the inspection of the current customs declaration. As inspection of customs declaration can take from hours to days, it is difficult to measure the workers' workload using a fixed time interval. *AgentWorkload* is measured by the amount of all customs declarations (all "lights", including yellow, red, and green) processed by the customs agent between the start of inspection and the end of inspection for the current customs declarations, and *InspectorWorkload* is measured by the amount of all inspected customs declarations (only yellow and red "lights") processed by the inspector during the same time period.

Research Model. We follow the traditional log-linear learning curve models adopted in the literature (e.g., Adler and Clark 1991, Argote 1999, Reagans et al. 2005, Thompson 2007). For agent *i*, inspector *j*, customs declaration *d*, and time *t*, the regression model we estimate is:

$$Log(InspectionTime_{ijdt}) = \beta_0 + \beta_1 Log(DyadExperience_{ijdt}) + \beta_2 Log(Line_d) + \beta_3 Log(Line_d) * Log(Dyad\_experience_{ijdt}) + \beta_4 Log(DutyRate_d) + \beta_5 Log(DutyRate_d) * Log(Dyad\_experience_{ijdt}) + \beta_6 Log(Line_d) * Log(DutyRate_d) + \beta_7 Log(Line_d) * Log(DutyRate_d) * Log(Dyad\_experience_{ijdt}) + \beta_8 Log(AgentOtherExperience_{idt}) + \beta_9 Log(InspectorOtherExperience_{jdt}) + \beta_{10} Sector_d + \beta_{11} House_d + \beta_{12} Channel_d + \beta_{13} Month_t + \beta_{14} Dayofweek_t + \beta_{15} Hour_t + \beta_{16} Log(AgentWorkload_{idt}) + \beta_{17} Log(InspectorWorkload_{idt}) + \gamma_{ij} + \varepsilon \qquad \text{--------------------} [3.1]$$

In the equation, γ_{ij} is the fixed-effect for the dyad comprised of agent *i* and inspector

j, and ε is the standard error. We estimate this regression using fixed effects panel data methods. In our analyses, we use heteroskedastic robust standard errors clustered by the dyad.

3.5 Results

3.5.1 Main Estimation Results and Test of Hypotheses

Table 3.1 contains the descriptive statistics of our data, including the mean, standard deviation, and the pair-wise correlation for our major variables. All variables in the tables are continuous and log-transformed.[23]

Table 3.1: Descriptive Statistics

	Variable	Mean	Std. Dev.	1	2	3	4	5	6	7
1	Log(Inspection Time)	6.988	1.538							
2	Log(Dyad Experience)	3.016	1.520	-0.108						
3	Log(Line)	1.858	1.697	0.051	-0.043					
4	Log(DutyRate)	-1.919	2.027	0.094	0.073	-0.040				
5	Log(Agent Other Experience)	6.578	1.511	0.019	0.613	-0.023	-0.008			
6	Log(Inspector Other Experience)	7.231	1.365	0.004	0.484	0.058	0.096	0.324		
7	Log(Agent Workload)	3.303	1.479	0.447	0.249	-0.005	-0.035	0.548	0.022	
8	Log(Inspector Workload)	2.914	0.794	0.480	0.177	0.027	0.140	0.104	0.365	0.259

[23] Due to space limitation, we do not include the descriptive statistics for the dummy variables in our regressions.

Table 3.2 presents our main estimation results. In Column 1, we include all the control variables except for *AgentOtherExperience* and *InspectorOtherExperience*. We also include the number of lines and the duty rate, because they are important drivers of inspection time. In Column 2, we add the agent-inspector dyads' experience working together, and the individual agents and inspectors' experience outside the current dyad. In Columns 3 and 4, we include the interaction terms of *Log(DyadExperience)* with *Log(Line)* and *Log(DutyRate)*, respectively. In Column 5, we include the two interaction terms at the same time. Finally, in Column 6, we include all interaction terms to test the full research model.

As our model includes interaction terms, we cannot directly evaluate our hypotheses with only the coefficients in the full model. We followed the standard statistical procedure (e.g., Greene, 2003) to test the main effects in the full model (appearing in Column 6 of Table 3.2). This requires differentiating equation [3.1] with respect to the particular effect and substituting the mean of the moderator variables in the expression.

Table 3.2: Main Estimation Results

DV: log(InspectionTime)	(1) Controls only	(2) Dyad and Individual Experience	(3) Complexity	(4) Goal Conflict	(5) Complexity and goal conflict	(6) Full Model
Log(Line)	0.0283***	0.0284***	0.0468***	0.0285***	0.0470***	0.0552***
	(0.0023)	(0.0022)	(0.0043)	(0.0022)	(0.0043)	(0.0063)
Log(Duty Rate)	0.0109***	0.0110***	0.0109***	0.0029	0.0026	-0.0031
	(0.0015)	(0.0015)	(0.0015)	(0.0032)	(0.0032)	(0.0053)
Log(Agent Other Experience)		-0.1154***	-0.1160***	-0.1152***	-0.1159***	-0.1159***
		(0.0132)	(0.0132)	(0.0132)	(0.0132)	(0.0132)
Log(Inspector Other Experience)		-0.0686***	-0.0693***	-0.0674***	-0.0680***	-0.0679***
		(0.0104)	(0.0104)	(0.0104)	(0.0104)	(0.0104)
Log(Dyad Experience)		-0.0860***	-0.0747***	-0.0813***	-0.0699***	-0.0646***
		(0.0077)	(0.0085)	(0.0082)	(0.0091)	(0.0100)
Log(Line) * Log(Dyad Experience)			-0.0061***		-0.0061***	-0.0108***
			(0.0014)		(0.0014)	(0.0022)
Log(Duty Rate) * Log(Dyad Experience)				0.0026*	0.0027*	0.0060**
				(0.0011)	(0.0011)	(0.0019)
Log(Line) * Log(Duty Rate)						0.0047*
						(0.0022)
Log(Line) * Log(Duty Rate) * Log(Dyad Experience)						-0.0026**
						(0.0008)
R-square (within)	0.5053	0.5100	0.5101	0.5100	0.5101	0.5102
R-square (overall)	0.3656	0.4254	0.4253	0.4253	0.4251	0.4255

1. Numbers in parentheses are robust and cluster standard errors.
2. Dyad fixed effects are included for all columns and N=323,520..
3. $^{+}$ p<0.1; * p<0.05; ** p<0.01; *** p<0.001
4. Due to space limitation, coefficients for dummy control variables and workload variables are unreported.

For H1, we obtain the marginal effect of *Log(DyadExperience)* on *Log(Inspection)*, which is negative and significant (β = -0.0862, $p < 0.001$). Thus, our first hypothesis is supported. The effect indicates that when the agent-inspector dyad's experience working together doubles, the time for the dyad to complete the inspection process for a customs declaration decreases by 5.8%.[24] Equivalently, compared to an agent-inspector dyad with no experience working together, a dyad with an average level of dyad experience will enjoy a 29.2% performance improvement.[25]

To test H2, we calculate the marginal effect of *Log(Line)* * *Log(DyadExperience)* on *Log(Inspection)*. The marginal effect is negative and significant (β = -0.0057, $p < 0.001$), and our H2 is supported. Quantitatively, when *Log(Line)* is one standard deviation above the mean, the doubling of an agent-inspector dyad's experience working together is associated with a 6.45% performance improvement for the dyad.[26] But when *Log(Line)* is one standard deviation below the mean, the doubling of dyad experience will improve their performance by only 5.2%.[27] The difference suggests that under a higher level of task complexity, the impact of dyad experience on dyad performance will be stronger.

Similarly, to test H3, we calculate the marginal effect of *Log(DutyRate)* * *Log(DyadExperience)* on *Log(Inspection)*. The effect is positive and significant (β = 0.0010, p

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[24] $1-2^{-0.0862}$

[25] The average level of dyad experience before log-transformation is 54.6646. The performance improvement is calculated by $1-54.6646^{-0.0862}$

[26] $1-2^{-0.0962}$

[27] $1-2^{-0.0770}$

< 0.05), hence our H3 is also supported. When *Log(DutyRate)* is one standard deviation above (below) the mean, an agent-inspector dyad's performance will improve by 5.69% (5.96%) for every doubling of their experience working together.[28] As shown in the numbers, under higher level of goal conflict, the impact of dyad experience on their performance will be weaker.

Finally, we examine the coefficient of *Log(Line)* * *Log(Duty Rate)* * *Log(DyadExperience)* to evaluate H4. The coefficient is negative and significant ($\beta = -0.0026$, $p < 0.01$). As we could see from H3, the mean effect of *Log(Duty Rate)* on the relationship between *Log(DyadExperience)* and *Log(InspectionTime)* is positive. Therefore, an increase in *Log(Line)* is associated with a decrease in this effect, and our H4 is supported.

3.5.2 Robustness Checks

We conduct several robustness checks to examine the consistency of our results. Table 3.3 reports the results.

[28] $1\text{-}2^{-0.0845}$ and $1\text{-}2^{-0.0887}$, respectively

Table 3.3: Robustness Checks

DV: log(InspectionTime)	(0) Main estimation results	(1) Complexity: # of tariff codes	(2) Complexity: # of sectors (4 digit)	(3) Complexity: # of sectors (2 digit)	(4) Complexity: # of sectors (HS Code)	(5) Goal conflict: Duty	(6) Calendar Days	(7) Linear Experience
Complexity	0.0552***	0.0387***	0.0413***	0.0533***	0.0700***	0.0078	0.0552***	0.0234***
	(0.0063)	(0.0083)	(0.0092)	(0.0118)	(0.0067)	(0.0128)	(0.0063)	(0.0037)
Goal Conflict	-0.0031	0.0024	0.0019	0.0017	-0.0029	0.0091*	-0.0031	0.0164***
	(0.0053)	(0.0039)	(0.0037)	(0.0037)	(0.0048)	(0.0044)	(0.0053)	(0.0025)
Dyad Experience	-0.0646***	-0.0764***	-0.0772***	-0.0783***	-0.0690***	-0.0914***	-0.0652***	-0.0006**
	(0.0100)	(0.0090)	(0.0089)	(0.0088)	(0.0092)	(0.0115)	(0.0100)	(0.0002)
Complexity * Dyad Experience	-0.0108***	-0.0070*	-0.0073*	-0.0085*	-0.0115***	0.0076+	-0.0108***	-6.49e-05***
	(0.0022)	(0.0028)	(0.0031)	(0.0039)	(0.0023)	(0.0042)	(0.0022)	(1.82e-05)
Goal Conflict * Dyad Experience	0.0060**	0.0031*	0.0031*	0.0030*	0.0054**	0.0022	0.0059**	2.07e-05*
	(0.0019)	(0.0013)	(0.0013)	(0.0013)	(0.0017)	(0.0015)	(0.0019)	(9.13e-06)
Complexity * Goal Conflict	0.0047*	0.0010	0.0028	0.0052	0.0067**	0.0043**	0.0047*	-0.0035**
	(0.0022)	(0.0031)	(0.0034)	(0.0043)	(0.0022)	(0.0016)	(0.0022)	(0.0010)
Complexity * Goal Conflict * Dyad Experience	-0.0026**	-0.0018+	-0.0021+	-0.0028+	-0.0032***	-0.0018**	-0.0026**	-4.39e-06**
	(0.0008)	(0.0011)	(0.0012)	(0.0015)	(0.0008)	(0.0005)	(0.0008)	(1.34e-06)
Calendar Days							0.0005+	
							(0.0003)	
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-square (within)	0.5102	0.5097	0.5097	0.5097	0.5103	0.5104	0.5102	0.5097
R-square (overall)	0.4255	0.4250	0.4248	0.4251	0.4247	0.4255	0.4125	0.3983

1. Numbers in parentheses are robust and cluster standard errors.

2. In Columns (1)-(6), we use the log-transformed values of experience in the estimation. In Column (7), we use the original value of experience.

3. $^{+}$ p<0.1; * p<0.05; ** p<0.01; *** p<0.001

4. Due to space limitation, coefficients for all control variables are unreported.

Similar to other studies, our results may be sensitive to the choice we have made in constructing our variables and selecting research models. One issue is whether our specifications of the task characteristics are robust. In Columns (1)-(4) of Table 3.3, we test alternative measures of task complexity. Our interviews with the customs agents suggest that the number of different types of goods involved in the customs declaration can also increase the complexity of inspection. Thus, we count the number of distinct tariff codes in the customs declaration as a measure of task complexity in Column (1). In addition, some tariff codes are very similar, and inspecting them together may not necessarily be more complex than inspecting goods with only one code. Therefore, we group the tariff codes and use the number of distinct groups in the declaration to measure task complexity. Based on 4-digit, 2-digit, and the 16 general sector categories defined in the Harmonized System Codes, we build our measures and report the results in Columns (2)-(4), respectively. In Column (5), we examine an alternative measure of task-level goal conflict, which is the amount of customs duty. Overall, the results are qualitatively similar, and our findings are consistent.

Another concern is that the perceived effect of dyad experience may be just a reflection of the passage of time (Argote, 1999; Reagans et al., 2005). To test this, we create a variable CalendarDay to measure the number of days that has passed since an agent-inspector dyad performed their first inspection task. As expected, it is highly correlated with the dyad's experience working together. Column 6 in Table 3.3 shows the results. Calendar day is positive and only significant at the 0.1 level, and other coefficients exhibit little change from the results in Column 6 of Table 2. Hence, under our setting, dyad experience is a better indicator of the dyad's learning to work with each other.

Finally, recent literature argues that learning curve may follow an exponential form rather than a power form (Lapre, Mukherjee, and Wassenhove, 2000; Lapre and Tsikriktsis, 2006). Although the exponential form is developed from the quality improvement model, we also test whether our results on *InspectionTime* are consistent under this form. The results are reported in Column 7 of Table 3.3. The signs of the coefficients are consistent with our main results, and the R-square is smaller. Generally, our findings are also robust under this model.

3.5.3 Post-hoc Analysis

To further verify our results and gain additional insights, we conduct a post-hoc analysis. In Costa Rica, customs agents may work as individuals or work for a brokerage firm. In addition, brokerage firms also vary greatly in their sizes. During our interviews with several large brokerage firms, we learned that those firms had very rigorous practices and rules for their agents. On the other hand, the small firms usually did not have those regulations. Thus, it could be possible that customs agents working for large firms exhibit a different pattern of learning to work with the customs inspectors.

To understand the impact of customs agents' organizational background on our findings, we conduct a split sample analysis in which we divide our sample by the size of the brokerage firm where the customs agent works. Based on the number of customs declarations processed, the average value of goods, and the average amount of customs duty, we adopt a k-means cluster analysis to identify 10 large brokerage firms from others. Based on the identification, we divide our sample into two sub-samples and run the regression [1] for each subsample separately. The results are presented in Table 3.4.

Table 3.4: Post-hoc Analysis Results

DV: log(InspectionTime)	(1) Large firm	(2) Small firm and self-employed customs agents
Log(Line)	0.0475***	0.0428***
	(0.0095)	(0.0075)
Log(Duty Rate)	0.0046	0.0001
	(0.0067)	(0.0067)
Log(Agent Other Experience)	-0.1412***	-0.0894***
	(0.0299)	(0.0130)
Log(Inspector Other Experience)	-0.0718***	-0.0834***
	(0.0163)	(0.0112)
Log(Dyad Experience)	-0.0159	-0.0660***
	(0.0133)	(0.0122)
Log(Line) * Log(Dyad Experience)	-0.0050+	-0.0113***
	(0.0027)	(0.0029)
Log(Duty Rate) * Log(Dyad Experience)	0.0038*	0.0084**
	(0.0019)	(0.0026)
Log(Line) * Log(Duty Rate)	0.0017	0.0029
	(0.0028)	(0.0028)
Log(Line) * Log(Duty Rate) * Log(Dyad Experience)	-0.0017*	-0.0025*
	(0.0008)	(0.0011)
Fixed effects	Yes	Yes
N	102,246	221,274
R-square (within)	0.5999	0.4936
R-square (overall)	0.5017	0.5032

1. Numbers in parentheses are robust and cluster standard errors.
2. $^{+}$ p<0.1; * p<0.05; ** p<0.01; *** p<0.001
3. Due to space limitation, coefficients for dummy control variables and workload variables are unreported.

Column 1 of Table 3.4 shows the regression results for dyads in which the customs agent works for any of the 10 large firms, and Column 2 shows the results for the rest of the dyads. The size of the large-firm subsample is about 1/3 of the entire sample. From Columns (1) and (2), we observe that the signs of the coefficients are consistent with the main estimation results, so our findings are robust for dyads with customs agents of different organizational backgrounds. In addition, we notice that the coefficients of

Log(DyadExperience) and all interaction terms are generally smaller in the large-firm subsample. The smaller coefficients imply that the impact of dyad experience is weaker when the customs agent in the dyad works for a large firm. One possible explanation could be that the large firms are able to provide many supporting services to the customs agents, so they will not rely so much on their own experience. In one interview, the manager of the large broker firm said that they only had 4 customs agents, but they employed around 80 workers to assist for the agents' work, such as collection of the original documents. In another interview of a multi-national customs brokerage firm, the regional director mentioned that they had 600 permanent employees and 300 temporary employees, working in areas of law services, operations, marketing, and logistics. All those employees help to support the work of the customs agents from certain aspects. In addition, the impact of task-level goal conflict on the relationship between dyad experience and dyad performance is weaker for agents from large brokerage firms. This may reflect the role of practices and regulations for those agents in the large brokerage firms. Under the existence of the regulations, the customs agents may have less incentive to minimize the customs duty, because they may lose their job once the behavior is discovered during the customs inspector's inspection. As a result, the level of goal conflict will also be lower for those agents. A further investigation to under the organizational context of those agents may provide more insights.

3.6 Discussion and Conclusions

3.6.1 Discussions

Our study has several key findings. First, we find that an increase in an agent-inspector dyad's experience working together is associated with a reduction in their time to complete the inspection process for a customs declaration. We have argued that this improved efficiency is enabled through the growing of experience working together, in which the dyad develops mutual understanding and trust with each other. One interviewee mentioned that: "When the inspectors work more with the customs agents, the inspectors can learn whether they are trustworthy or not, and they like dealing with those who are trustworthy … Having a good relationship with the inspector can help to reduce the time of the inspection process …" As the customs automation system eliminates the opportunity for the customs agents to develop their relationship with the inspectors, the only way to build a solid relationship and trust is through increasing their experience working together on the inspection tasks. Thus, under our setting, the dyad experience plays an important role on their task performance.

Second, we find that the impact of dyad experience on their performance varies across different tasks. Our results suggest that an agent-inspector dyad's experience is associated with a greater level of performance improvement when the customs declaration to be inspected has more lines of goods. The results also show that the dyad experience improves their performance more for customs declarations with higher duty rate. We draw the learning curves of an agent-inspector dyad for high-complexity and low-complexity tasks in the left panel of Figure 3.3, and curves for high-conflict tasks and low-conflict tasks in the right panel of Figure 3.3.[29] As depicted in the figure, the dyad's learning curve is steeper under high level of complexity and under low level of goal conflict. The steeper

[29] We plot Figure 3.3 using mean plus one standard deviation for high values of task complexity and goal conflict and mean minus one standard deviation for low values. We also use the same values in Figure 3.4.

learning curve for high-complexity tasks is perhaps because that under our setting, more lines of goods (i.e., higher complexity) mean that more things need to be inspected. When the agent and inspector have more experience working together, they may be able to develop a better schema to distribute their work for inspecting different lines of goods. On the other hand, extensive experience working together may not be as necessary for simple tasks, and could be less beneficial when there are only several lines of goods in the declaration. In addition, for customs declarations that are subject to a higher duty rate (i.e., higher goal conflict), the relationship between the customs agent and the customs inspector may not be as helpful, given their diversity in the goods. In addition, their communication will be less effective, because higher duty goods usually require more debates and more time to resolve. Those results suggest that it is important to consider the role of different task characteristics in understanding the relationship between dyads' experience working together and their task performance.

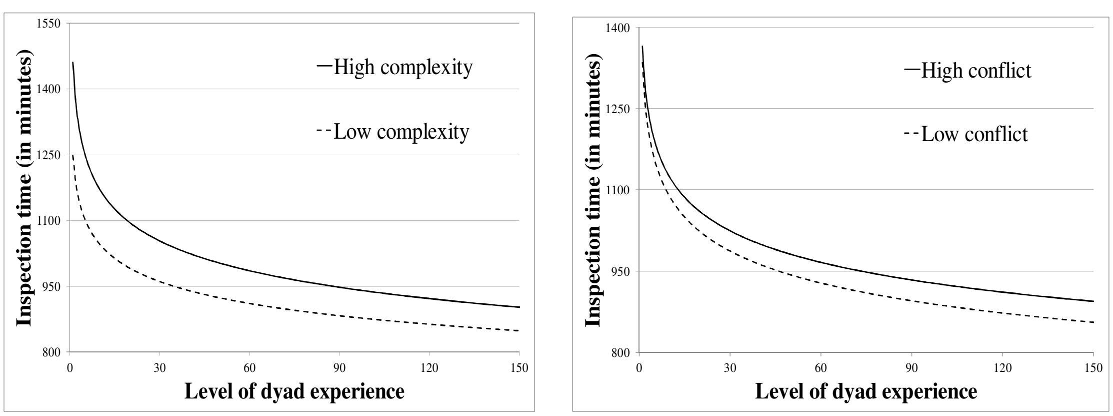

Figure 3.3: Task Complexity, Task-Level Goal Conflict, and the Impact of Dyad Experience on Inspection Time

Third, we find that task complexity and task-level goal conflict not only affects the relationship between dyad experience and dyad performance separately, but also has a joint effect on the relationship. Figure 3.4 demonstrates the dyad's learning curve for tasks with different combinations of task complexity and task-level goal conflict. It is as expected that when the dyad has no experience working together, the performance will be the worst for a high-complexity, high-conflict task, and will be the best for a low-complexity, low-conflict task. Also, not surprisingly, we notice that the dyad learning curve for a low-complexity, high-conflict task is the flattest. Interestingly, we find that the dyad learning curve for a high-complexity, high-conflict task is steeper than all other three learning curves. One possible explanation is that the increasing amount of lines of goods motivates the communication between the agent and the inspector. Through the communication, the agent-inspector dyad can resolve issues embedded with the goods that is subject to higher duty rate. Further, during the issue resolution process, the dyad can also identify approaches to deal with the huge number of goods lines. All those benefits can be achieved more when the dyad has more experience working together, because they will have a better understanding of each other and their communication will be more efficient. Those results further establish that the impact of task characteristics on dyad learning is very complex. We should not only consider the effect of individual task characteristics but also their joint effects.

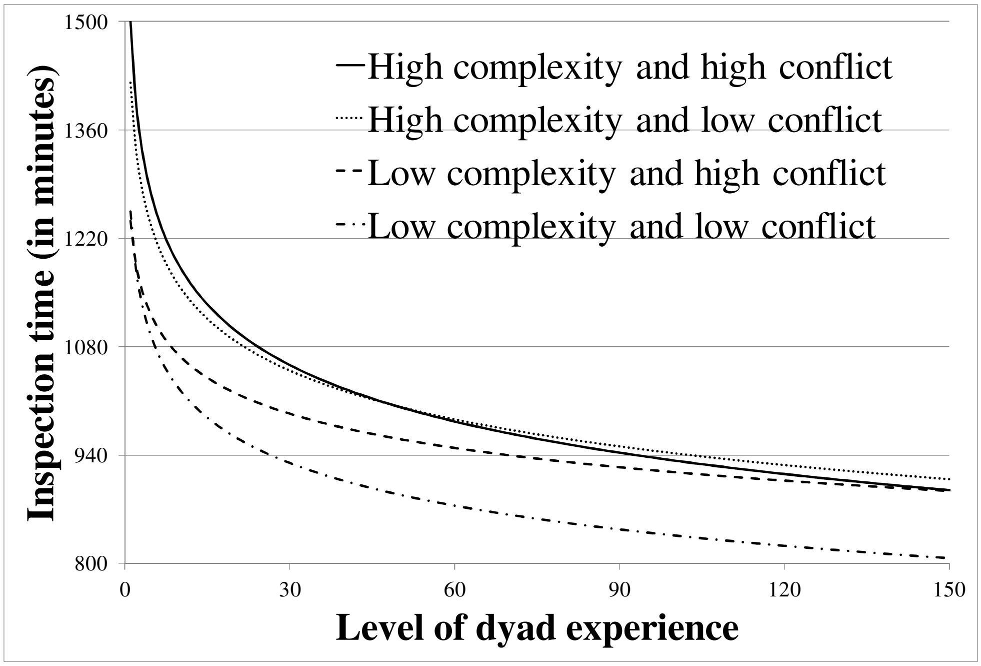

Figure 3.4: Dyad Learning Curve under Different Combinations of Task Complexity and Task-Level Goal Conflict

Finally, our post-hoc analysis suggests that organizational context of individuals in the dyad can also affect the impact of dyad experience on their performance, as well as the moderation effects of different task characteristics. Similar to Figure 3.4, we depict the dyad's learning curve under different levels of task complexity and goal conflict for the two subsamples in Section 5.3.[30] In Figure 3.5, the left panel shows the learning curves for the large-firm subsample, and the right panel shows the learning curves for the rest. Clearly, the learning curves for dyads with agents working for large brokerage firms are much

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[30] We use the same high and low values of task complexity and task-level goal conflict in both panels of Figure 3.5. Although the subsamples vary in the summary statistics of the two variables with the full sample, using subsample-based high and low values may make the comparison between the two subsamples infeasible.

flatter, suggesting that dyad experience plays a smaller role in those dyads' task performance. According to our interviews, the results may imply that the substitution effect of the supporting services offered by the large firms on the customs agents' experience working with the inspectors. Similarly, when the agents from large brokerage firms face more complex tasks, they may also rely on the supporting services rather than their experience with the inspectors, thus the moderation effect of task complexity is also weaker. Further, we find that the moderating role of task-level goal conflict is weaker when the agent in the dyad works for a large brokerage firm. This is possibly because large firms have stricter regulations to control the customs agents' behavior, so the agents will conform more to the policies and have less goal conflict with the customs inspectors. Summarizing those results, we find that it is also important to understand the role of the individuals' organizational context in the dyad learning effect. Future work can build on this observation to further investigate how organizational context of individuals in the dyad affects the dyad's learning to work with each other in more detail.

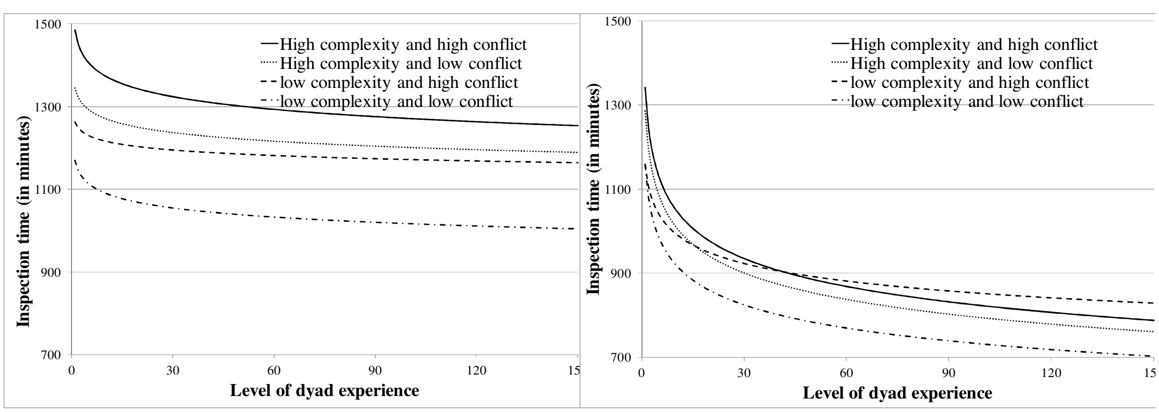

Figure 3.5: Dyad Learning Curves for Dyads with Agents Working for Large Firms versus Dyads with Agents Working for Small Firms

3.6.2 Conclusions and implications

Our study examines the dyad learning effect in co-produced service tasks. In particular, we also investigate how this effect varies under tasks with different levels of complexity and goal conflict. In so doing, we make several theoretical contributions.

First, we provide evidence on the existence of dyads' learning-by-working-together in service tasks, which has been growing in importance. In particular, we help to advance the understanding on how such learning-by-working-together effect influences dyads' task performance when there are goal conflicts within the dyads. Although several prior studies examine how team members' experience working with each other affects team performance (e.g., Boh et al., 2007; Espinosa, Slaughter, Kraut, and Herbsleb, 2007; Huckman and Staats, 2011; Huckman, Staats, and Upton, 2009; Reagans et al., 2005), the team members in those studies come from the same organization, share the same goal, and exhibit less conflicts with each other. When the individuals in the dyad have extensive goal conflicts, the impact of their experience working together remains less understood. Further, as conflicts within the dyad usually lead to inferior dyad performance (Cosier and Rose, 1977; De Dreu and Weingart, 2003; de Wit et al, 2012; Simons and Peterson, 2000), it is important to find solutions to mitigate their effects. Our results suggest that increasing repeated interactions within the dyad may be a good solution. Future work should investigate the underlying mechanisms why repeated interactions within dyads are associated with the reduction in different types of conflicts.

Second, we further demonstrate the importance of understanding the role of task characteristics in the dyad's learning-by-working-together. While prior learning curve studies invested significant effort to uncover the impact of different types of experience on task performance (e.g., Boh et al., 2007; Clark et al., 2012; KC and Staats, 2012; Schilling, Vidal, Ployhart, and Marangoni, 2003; Staats and Gino, 2012), it remains unclear whether experience has different impacts for tasks with different characteristics. Our research fills this gap by studying how the effects of a dyad's experience working together varies when tasks have different levels of complexity and goal conflict. We find that the dyads' cooperation experience is more effective for high-complexity tasks and low-conflict tasks. Further, we notice that for high-complexity, high-conflict tasks, there may be a joint effect to increase the impact of dyads' experience working together on their performance. Our results highlight that we need to understand not only how individual task characteristics (e.g., task complexity and task-level goal conflict) influence the dyad's learning, but also how the task characteristics interact with each other.

Third, we show that the organizational context of the individuals in the dyad may also matter for the dyads learning-by-working-together. We respond to the call for research to enhance the understanding in learning under different organizational contexts (Argote and Miron-Spektor, 2011). Prior literature suggests that organizations with more experience working with the client can help with the individual employee's performance working with that client, but it may also be a substitute for individual experience (Clark et al., 2012). From another perspective, our results suggest that customs agents from large brokerage firms benefit less from their experience working with the inspectors.[31] Our

[31] In our setting, the learning is bilateral, and both the customs agent and the customs inspector have to learn. Thus, although it is possible to calculate the organizational experience for an agent (inspector) with a certain inspector (agent), the variable can affect the dyad performance in two ways. It can be viewed as the amount of an individual's experience with other partner individuals in the same corporation where her focal partner works, thus reflecting a knowledge transfer effect across different types of individual experience. It can also

interviews point to one possible explanation that the large firms offer many supporting services to the agents, which may work as another substitute of experience. Further studies should explore how the availability of organizational support to the individuals influences their learning to work with their partners.

Our study also has practical implications. Our results suggest that the agent-inspector dyad's experience exhibits the strongest impact on their performance for high-complexity, high-conflict tasks, and has the least effect for low-complexity, high-conflict tasks. Therefore, to improve the customs inspection efficiency, the customs can modify the algorithm to assign inspectors in the customs automation by making the system assign customs declarations with more lines and higher duty rate to inspectors who have more experience working with the customs agent processing it, and assign declarations with less lines and higher duty rate to inspectors who have fewer interactions with the agent. This modification in the system algorithm may potentially reduce the inspection time for customs declarations.

Our research is not without limitations. First, while our setting controls for many factors that can influence the internal validity of our results, it may also limit the generalizability of the findings. While we note that our findings are likely relevant for a wide range of service settings where tasks are completed by dyads (e.g., consulting, auditing, or legal services), further studies should attempt to validate the findings under

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be perceived as the amount of an individual's organization experience with her focal partner, and it implies a knowledge spillover effect between individuals from the same organization. The two effects are mingled together and cannot be separated. As a result, we do not specifically examine the impact of organization experience on dyad performance.

other contexts. Second, while we concentrate on understanding how the dyads' experience affects their completion time, other performance measures may be interesting to examine. Third, while we use fixed-effects to control for time-invariant characteristics of the individual customs agents and customs inspectors, our results may still be subject to concerns of bias due to other sources of endogeneity. Nonetheless, our interviews suggest that the inspector assignment to work with different customs agents is random. In addition, while customs agents may be assigned to tasks with different levels of complexity and goal conflict, the trend in our data suggests that the endogeneity from such assignments leads to opposite results.[32] Future research can exert higher control over task assignment by using laboratory or field experiments. Finally, while our setting ensures that the measure of dyad experience working together reflects exactly the number of interactions between the customs agents and the customs inspectors, the realities of our data prevent us from observing what takes place during each interaction. The meeting and subsequent communication in the customs inspection process is very private, and we are not allowed to view the contents of communication messages stored in the system. Future work can enrich the understanding of the dyads' learning-by-working-together by investigating the communication patterns during the interactions within the dyads.

[32] We expect that the time-varied ability of the individual customs agents may affect the dyad's learning rate, such that better agents exhibit a higher learning rate from dyad experience. Further, as individual agents can accumulate task knowledge through their experience on the task, we examine whether task complexity and task-level goal conflict are affected by the agent's, the inspector's, and the dyad's experience in customs inspections. We find that contrary to common wisdom, more complex tasks are assigned to agents with less experience. In addition, as expected, we observe that tasks with higher levels of goal conflict are assigned to agents with more experience, but this implies a higher learning rate of the dyad rather than a lower learning rate which we argue in H3.

APPENDIX A

FOR CHAPTER 2: STEPS FOR GENERATION OF THE VARIABLE RELATEDNESS

We construct the measure of experience relatedness to the current task based on two facts. First, the interviews with the customs agents suggest that the customs declaration tasks contain knowledge on different dimensions, such as the regime (import or export) or the type of goods involved. Second, although two different tasks may belong to different categories in those dimensions, they still have certain commonalities in the procedures and policies. Thus, we follow a unique approach to generate the variable of *Relatedness*. We also attempted different alternatives in the variable generation process to evaluate its robustness.

Step 0: Identify dimensions to describe the task and corresponding variables for each dimension

Based on the interviews, we identify four dimensions that may lead to differences in the task completion: the regime of the declaration, the customs house where the agent submitted the declaration, the client (i.e., the importer or exporter), and the type of goods. There are huge differences in the rules and processes for different regimes, so regime is an important dimension in our calculation of relatedness. For different customs houses, customs declarations usually adopt different transportation media for goods from different countries. For example, declarations submitted to the border houses are usually transported by land from the neighboring countries (e.g., Nicaragua and Panama), while declarations processed at the port houses are more likely to transport by sea from North America and

East Asia. This can also lead to variations in the processes, such as documents to submit and approvals required. Our interviews also indicate that different types of clients may submit different kinds of original documents, which causes deviations in the task completion. While large clients tend to submit electronic versions of very standard originals, small clients create a lot of difficulties, because their originals will have significant variations in the formats. The type of goods involved also brings differences in task completion, because certain goods such as live animals or chemical products will require technical approval requests to different government institutions.

We also identify the type of variables used in the data to represent those dimensions. Regime, customs house, and client are identified by three categorical variables: *Regime, House,* and *Client.* Type of goods is represented by a vector of 16 dummy variables *Sector* indicating whether a specific sector of goods (for example, foodstuffs or textiles) is included in the declaration. One declaration will belong to only one regime and one customs house, and is from one single client, but can contain multiple sectors of goods. For the range of those categorical variables, we have:

$$Regime \in R\{Import, Export, Transit, FreeTrade\}$$

$$House \in H\{Central, Caldera, Penas\ Blancas, Santamaria, Limon, Paso\ Canoa\}$$

$Client \in C\{00010242K, 00012244K, \ldots, ZZ187044\}$ (In total, we have 99,899 distinct clients)

Step 1: Identifying relatedness measure for each of those dimensions

In our setting, we have four dimensions for each single task. Three of them are represented by categorical variables, and one is represented by a vector of binary variables. Thus, we will choose corresponding dimension-level relatedness measures based on that.

For categorical variables, the simplest way is to set relatedness between the two observations equal to 1 if the values are identical and 0 if not. However, as we have context information on the meaning of different values for those variables, we choose a more informative approach. We first search for continuous variables that can be used to describe the categorical values. For variables with different scales, we will normalize them. After that, we use those variables to calculate the Euclidean distance between two categorical values in the same dimension. As the distance has a range of $[0, +\infty)$, we then convert it to a relatedness measure of [1, 0].

For regime, we use the timeline of system implementation as a proxy. Costa Rican government adopted a phased approach to implement the customs automation system, and different regimes were implemented at different time points. According to system implementation literature, in phased implementation of information systems such as ERP, one important factor driving the module sequencing decision is the alignment of system and business (Hallikainen, Kivijarvi, and Tuominen, 2009). It is not a one-time decision, but a lasting processing in the systems implementation. When some modules have already been implemented, the next step is usually to implement a related module, as the related module is more aligned with the existing modules and the business. Our interviews also reinforced this notion: the last regime implemented in our data collection period was the FreeTrade regime, which was the most distinctive regime with very specific rules and procedures. We also noticed that several specific regimes were implemented recently, and they are all very different from the existing regimes.

For customs houses, we calculate the distance between different customs houses using the distribution of transportation media and countries where the commodities are from or go to. Our interviews suggest that the transportation medium and the countries affect the format of the originals and the deliverables to the system. For example, there are treaties between Costa Rica and the European Union that restrict the input of some data fields in the system to certain ranges, and violations will lead to huge amount of penalty.

For client, our interviews show that size is an important factor differentiating the clients' behavior which may affect the task completion. Therefore, we choose the total number of declarations sent to the agents, the average value of goods per declaration, and the average customs duty per declaration to measure the size of the client. As we have almost 100,000 clients, differences between most of those clients may not imply differences in the behavior. To address this, we first conduct a k-means cluster procedure to categorize the clients. Using the Calinski-F Stat as the stop rule, we find 7 clusters for the clients. Table A.1 represents the summary statistics for the 7 clusters.

Table A.1: Summary Statistics of Client Clusters

Client Clusters	Number of clients	Volume of transaction	Average value of goods	Average customs duty
Missing client information	1	290,571.00[1]	0.00[1]	0.06[1]
Very Big Clients	17	1,093.88	1,237,969.00	23,602.27
Big Clients	3	374.00	6,883,178.00	295,593.30
Medium clients_More volume	2,841	78.31	35,255.13	9,934.86
Medium clients_Larger value	122	47.69	183,198.70	35,805.42
Small Clients	28,264	25.40	8,020.40	3,209.45
Very Small Clients	68,651	17.17	2,761.53	534.89

1. Values are before normalization

After the clustering processing, we re-define the client variable as *ClientCluster* that:

$$ClientCluster \in \{Missing, Very\ Big, Big, Medium\ Volume, Medium\ Value, Small, Very\ Small\}$$

Then we calculate the distance between two client clusters using the average of all Euclidean distances between pairs of clients "C_1" from one cluster and "C_2" from the other. After generating the distances, we then convert them to a relatedness measure which ranges from zero to one. Literature suggests several possible conversion functions. The function R should satisfy two conditions. First, the function R is monotonic decreasing function. Second, $R(0) = 1$ and $R(+\infty) = 0$. Strehl (2002) proposed that $R = e^{-Distance^2}$ had important desirable properties for analysis than most other functions, and we choose it as our base conversion function. We also attempt other conversion functions, such as $R = e^{-Distance}$ (Shepard, 1987) and $R = \frac{1}{1+Distance}$ (Strehl, 2002).

For sector, as it is represented by a vector of binary variables, we use the Jaccard Index to calculate the relatedness between two tasks (Jaccard, 1901). For task *i* and task *j*, we have:

$$Relatedness^{Sector}(i,j) = \frac{\sum_{k=1}^{16} I(Sector_k(i) = Sector_k(j) = 1)}{16 - \sum_{k=1}^{16} I(Sector_k(i) = Sector_k(j) = 0)}$$

Step 2: Calculate dimension-relatedness of all prior experience to the current task

In this step, we calculate the dimension-relatedness for the current task by averaging the values of dimension-relatedness to the current task for all prior tasks processed by the same agent. For task *d* processed by agent *i*, we have:

$$Relatedness_{id}^{Dimension} = \overline{Relatedness^{Dimension}(d,d')}, d' < d$$

$$Dimension \in \{Regime, House, ClientCluster, Sector\}$$

For example, assume the relatedness between import regime and export regime is 0.5. The current task is import regime and the agent has processed 100 tasks in import regime and 50 tasks in export regime. Thus, the regime-relatedness for the current task will be (100*1+50*0.5)/150=0.83.

Step 3: Calculate overall-relatedness of all prior experience to the current task

For overall relatedness, we first calculate the Euclidean distance between all prior experience and the current task, which is:

$$Distance_{id} = \sqrt{\sum_{Dimension} (1 - Relatedness_{id}^{Dimension})^2},$$

$$Dimension \in \{Regime, House, ClientCluster, Sector\}$$

The range of this distance will be from 0 to 2[33], so we use the function below to convert it to the overall relatedness:

$$Relatedness_{id} = \frac{2 - Distance_{id}}{2 - 0}$$

Under this measure, when the agents' prior experience is completely unrelated to the current task, the four dimension-relatedness variables will equal to 0, the distance will equal to 2, and the overall relatedness will equal to 0. On the other hand, if the agents' prior experience is always the same as the current task, the four dimension-relatedness variables will equal to 1, and the distance will equal to 0, and the overall relatedness will equal to 1. For robustness, we also attempt to calculate the overall relatedness as the average of four individual dimension-relatedness measures. In addition, we switch the sequence of step 2 and step 3, and the results are generally consistent.

[33] $\sqrt{1+1+1+1}$

APPENDIX B

FOR CHAPTER 2: RESULTS USING FOCAL EXPERIENCE AND RELATED EXPERIENCE VARIABLES

Following prior literature (e.g, KC and Staats, 2012; Staats and Gino, 2012), we classify the customs agents' experience into focal experience and related experience to perform a comparative analysis. We define focal experience as the cumulative number of declarations processed by the focal agent with the same regime, the same customs house, the same client, and the same sector as the current task, and related experience as the total experience subtracts the focal experience. Then we test the following research models:

$Log(TimeComplete_{id}) = \beta_0 + \beta_1 Log(FocalExperience_{id}) + \beta_2 Log(RelatedExperience)_{id} + \beta_3 Sector_d + \beta_4 Log(Line_d) + \beta_5 Log(Value_d) + \beta_6 Log(AgentWorkload_{id}) + \beta_7 Dayofweek_d + \beta_8 Year_d + \beta_9 Hour_d + \beta_{10} ImplementationShock_d + \beta_{11} Log(SysWorkload_d) + \gamma_i + \varepsilon_{id}$

------------------*[B.1]*

$Inspection_{id} = \beta_0 + \beta_1 Log(FocalExperience_{id}) + \beta_2 Log(RelatedExperience)_{id} + \beta_3 Sector_d + \beta_4 Log(Line_d) + \beta_5 Log(Value_d) + \beta_6 Log(AgentWorkload_{id}) + \beta_7 Dayofweek_d + \beta_8 AgentHistory_{id} + \beta_9 BrokerHistory_d + \beta_{10} ClientHistory_d + \beta_{11} OverallInspectionRate_d + \gamma_i + \varepsilon_{id}$ -----------------*[B.2]*

The results are summarized in table B.1.

Table B.1: Summary of Results for Focal Experience and Related Experience

	(1)	(2)
	DV: Log(TimeComplete)	DV: Inspection
Log(Line)	0.0225***	0.0654***
	(0.0062)	(0.0050)
Log(Value)	0.0217***	0.0098***
	(0.0039)	(0.0013)
Log(Focal Experience)	0.0112**	-0.0035*
	(0.0037)	(0.0016)
Log(Related Experience)	-0.0734***	0.0006
	(0.0138)	(0.0010)
Fixed effects	Yes	Yes
N	998,258	998,258
R-square (within)	0.0787	0.1750
R-square (overall)	0.0768	0.2464

Comparison of findings

Our approach	Moderate level of relatedness is the best	Higher level of relatedness is better
Traditional approach	Related experience is more beneficial	Focal experience is more beneficial

Our results suggest similar implications for quality (i.e, likelihood of inspection), as our measure of relatedness follows a linear relationship with the likelihood of inspection. However, we suggest that a moderate level of relatedness would be better for completion time, whereas the traditional approach implies that related experience is beneficial and focal experience is not. Clearly, our results provide some additional insights into the impact of relatedness, because when we use the continuous measure, we are able to test for more nuanced relationships, such as curvilinear relationships.

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