Essays on the Impacts of IT on the Nature of Work

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ABSTRACT

As diverse information technology (IT) tools and systems are widely used at workplaces, IT has brought about fundamental changes to various aspects of work. Even though there is a significant body of literature on the topic, our understanding of how IT influences the nature of work remains incomplete. In this dissertation, I write two essays that examine the impact of IT on two specific aspects of work related to coordination: specialization (the degree of narrowness of individual worker's task scope) and urban agglomeration (the degree of the concentration of employment in urban areas). I draw on the perspectives of coordination costs and skill-biased technical change (SBTC) to theorize and empirically examine the impacts of IT on these two aspects of work. The findings suggest that while IT increases the degree of specialization and urban agglomeration, the impact of IT is moderated by several occupational characteristics, demonstrating the contingent nature of the impacts of IT. This dissertation makes several contributions. First, it provides a comprehensive theoretical framework based on the coordination and SBTC literatures for understanding how IT influences the specialization and urban agglomeration of work. Second, compared to prior studies, this research provides broader and more direct empirical evidence on the impact of IT on the degree of specialization and urban agglomeration as well as the moderating effect of occupational characteristics, thereby advancing our understanding of the impact of IT on the nature of work. Third, I highlight the double-edged nature of IT related to coordination costs: although IT can decrease coordination costs by facilitating the exchange of information, IT can also increase coordination costs by making a production process more complex.

Keywords: Information technology, nature of work, skill-biased technical change, specialization, urban agglomeration, coordination

ABSTRAIT

Étant donné que divers outils et systèmes de technologie de l'information (TI) sont largement utilisés sur les lieux de travail, les TI ont entraîné des changements fondamentaux dans divers aspects du travail. Même s'il existe une importante littérature sur le sujet, notre compréhension de la façon dont les TI influencent la nature du travail reste incomplète. Dans cette thèse, j'écris deux essais qui examinent l'impact de l'informatique sur deux aspects spécifiques du travail liés à la coordination : la spécialisation (le degré d'étroitesse de la portée de la tâche d'un travailleur individuel) et l'agglomération urbaine (le degré de concentration de l'emploi dans les zones urbaines). domaines). Je m'appuie sur les perspectives des coûts de coordination et du changement technique axé sur les compétences (SBTC) pour théoriser et examiner empiriquement les impacts de l'informatique sur ces deux aspects du travail. Les résultats suggèrent que si les TI augmentent le degré de spécialisation et d'agglomération urbaine, l'impact des TI est modéré par plusieurs caractéristiques professionnelles, démontrant la nature contingente des impacts des TI. Cette thèse apporte plusieurs contributions. Premièrement, il fournit un cadre théorique complet basé sur la littérature de coordination et de SBTC pour comprendre comment les TI influencent la spécialisation et l'agglomération urbaine du travail. Deuxièmement, par rapport aux études antérieures, cette recherche fournit des preuves empiriques plus larges et plus directes sur l'impact des TIC sur le degré de spécialisation et l'agglomération urbaine ainsi que sur l'effet modérateur des caractéristiques professionnelles, faisant ainsi progresser notre compréhension de l'impact des TIC sur le nature du travail. Troisièmement, je souligne la nature à double tranchant de l'informatique liée aux coûts de coordination : si l'informatique peut réduire les coûts de coordination en facilitant l'échange d'informations, elle peut également augmenter les coûts de coordination en rendant un processus de production plus complexe.

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CONTRIBUTION TO ORIGINAL KNOWLEDGE

This thesis contributes to the previous literature in many ways. This thesis investigates the relationship between IT usage and the coordination costs using two different novel measure, the degree of specialization and the degree of urban agglomeration. The first essay provides an integrative theoretical framework on the relationship between IT usage and the degree of specialization which can explain both positive and negative impacts of IT on specialization. It also provides a new body of empirical evidence that IT facilitates the worker specialization. The second essay provides a new body of evidence that IT facilitates the degree of urban agglomeration. It also theorizes and provides empirical evidence that the overall effect of IT usage on urban agglomeration is positively moderate by the complex communication task intensity and complex manual task intensity. Finally, this thesis in overall articulate and provides a new body of evidence supporting two countervailing mechanisms for both positive and negative effects of IT on the coordination costs.

CONTRIBUTION OF AUTHORS

The first author of all manuscripts included in this thesis is Insung Hwang. The co-author of the

All manuscripts is Dr. Kunsoo Han. The main contributions of the first author are to initiate, research and write the manuscripts in their entirety. The main contributions of the co-authors are to help brainstorming ideas, provide feedback and review manuscripts to improve the narrative and writing of the essays.

INTRODUCTION

Information technology (IT) has fundamentally changed the nature of work in terms of work content, process, and organization (Forman et al. 2014). Prior studies have found that IT changes the geographical distribution of work (Fabian et al. 2020; Gaspar and Glaeser 1998; Leamer and Storper 2001), task types (Acemoglu and Autor 2011; Autor et al. 2003), and organizational structure (Bresnahan et al. 2002; Leonardi 2007). Despite the current knowledge accumulated on how IT changes the nature of work, our understanding of the impacts of IT remains incomplete. Particularly, although it is well established that technical changes led by IT may critically affect the coordination of work within and between organization, we have a limited understanding of how such technical changes affect the way work is organized by chaining coordination costs. In this dissertation, I focus on investigating whether and how IT affects two specific aspects of work related to coordination: specialization (the degree of narrowness of task scope), and urban agglomeration (the degree of concentration of work activities in urban areas). By doing so, I aim to advance our understanding of the impacts of IT on how work is organized from a coordination perspective.

Prior research has examined how IT changes work by mainly focusing on the role of IT as a coordination technology or a skill-biased technology (Schweikl and Obermaier 2020). For example, Gurbaxani and Whang (1991) argued that IT improve coordination among co-workers by reducing costs for monitoring, contract, and communication. Such IT-induced changes in coordination has been extensively investigated by IS and economics literature on such topics as outsourcing and offshoring (Acemoglu and Autor 2011; Chang et al. 2015; Han and Mithas 2013; Liu and Aron 2014; Mithas and Whitaker 2007; Tambe and Hitt 2012) and organizational changes (Bresnahan et al. 2002; Brynjolfsson et al. 1994a; Malone 1987; Nault 1998). In these lines of studies, the central function of IT in changing the nature of work is to allow co-workers to exchange more information and hence improve their coordination. Another important finding in the previous literature is that IT brings about a skill-biased technical change (SBTC). That is, IT can substitute for simple routine tasks by automating and offshoring them, and complement complex non-routine tasks, thereby making tasks more complex and skill intensive (Acemoglu and Autor 2011; Acemoglu and Restrepo 2018; Autor et al. 2003). These lines of studies suggest that IT is fundamentally changing how people work with other workers as well as with machines.

While previous studies provide important insights regarding how IT changes the nature of work, little attention has been paid to examining whether such IT-induced changes increase or decrease coordination costs. While IT usage can improve coordination by reducing the costs to exchange information, the main argument of the SBTC literature implies that IT increases the amount of information to be exchanged (to reduce the information asymmetry for teamwork), thereby increasing coordination costs, as the new complex tasks created by IT require greater levels of skills or knowledge (Autor et al. 2003; Spitz-Oener 2006). However, there have been only few studies (Storper and Venables 2004) that theoretically or empirically investigate how the SBTC affect the coordination of work. Therefore, it is not clear whether IT increases or decreases coordination costs.

One of the key challenges in investigating how IT usage affects the coordination of work is that coordination costs cannot be easily observed or measured. As coordination occurs through diverse mechanisms such as communication, monitoring, contract, and standardization, it is impossible to directly measure the costs incurred for coordination. To tackle such challenges, this dissertation investigates the impact of IT usage on two observable measures related to coordination: the degree of specialization and the degree of urban agglomeration.

The degree of specialization, which refers to the narrowness of the task scope, is closely related to coordination costs because a worker's optimal degree of specialization is determined by the coordination costs incurred by the worker in the division of labor system the worker belongs to (Becker and Murphy 1992). Therefore, investigating the impact of IT on the degree of specialization would enhance our understanding of how IT affects coordination costs within and across individual workers. Similarly, the degree of urban agglomeration, which refers to the degree of the concentration of work activities in urban areas, is also closely related to coordination costs. While workers can improve coordination (or division of labor) by exchanging information and materials more efficiently using the physical proximity provided by urban areas, urban agglomeration increases other costs due to such concentration (e.g. high congestion costs or living costs) (Marshall 2009). Therefore, if the dominant effect of IT is to decrease coordinating costs, workers would be able to de-agglomerate by using IT to avoid the high costs they incur in the urban areas.

Given those two aspects of work are closely related to and heavily influenced by coordination costs, examining the impacts of IT on specialization and urban agglomeration will enrich our understanding of how IT affects coordination and coordination costs. To this end, this dissertation develops an integrative theoretical framework based on coordination perspective regarding the impacts of IT on coordination costs, and then empirically examines how IT affects the degree of specialization and the degree of urban agglomeration. By doing so, this dissertation advances the state of knowledge on the impacts of IT on how work is organized and coordinated.

The first essay investigates the relationship between IT and specialization. Specialization – the degree of narrowness concerning workers' task scope – has been a key foundation for the prosperity of modern society by allowing workers to routinize their jobs. Through repetition, workers can accumulate more experience and knowledge in a narrow task scope, which makes them more proficient and productive. Therefore, an economic system can grow with increasing specialization and division of labor. Not surprisingly, specialization has been an important topic in the fields of economics and organizational studies. However, few studies have examined whether and how IT affects specialization. This study develops a conceptual framework on specialization based on previous research in organization science and economics and theorizes how IT can influence worker specialization. In addition, I examine how the impact of IT on specialization varies depending on two occupational characteristics: cognitive skill level and the degree of urban agglomeration. I empirically validate our arguments by using occupational-level data from the Occupational Network (O*NET). I find that IT use is positively associated with the degree of specialization. Indeed, this relationship is stronger for occupations requiring higher cognitive skills and occupations that are more likely to be located in urban areas. Implications for research and practice are discussed.

In the second essay, I investigate the relationship between IT and urban agglomeration. Cities have been an important part of the modern economic system. Based on the physical proximity that the urban areas provide, workers can form complex and productive division-of-labor systems in the agglomerated areas. Some predicted that information technology (IT) would weaken the tendency to be agglomerated by substituting for the benefits of physical proximity in coordination. As a result, the "IT revolution" was expected to decrease the advantages of cities. However, cities have prospered over the past two decades despite the rapid technological changes. This study investigates this paradoxical effect of IT on urban agglomeration from a coordination perspective. Specifically, I examine how IT changes workers' optimal locations by changing the nature of their jobs and how this effect is moderated by occupational characteristics related with coordination. I empirically validate our arguments by using occupational-level data from US. This study contributes to the literature on agglomeration economies and routine-biased technical changes by demonstrating that IT facilitates urban agglomeration of jobs, and such effects are differential according to two occupational characteristics, worker's coordination intensity and problem-solving skill.

CHAPTER ONE – Does IT Facilitate Specialization? An Empirical Analysis

1. Introduction

Specialization has been an important principle underlying the modern economic system. By dividing a task into many subtasks and allocating each subtask to a worker, workers can be more proficient in the narrow scope of their tasks. Such a division of tasks not only reduces the difficulty of performing the subtasks, but also allows a worker to accumulate skills to perform the subtask better through repetition and develop new labor-saving tools and technologies. In *Wealth of Nations* (Smith 2010), Adam Smith begins with an introduction regarding the impact of this integral principle on productivity. In his famous example of a pin factory, he showed that factory workers can increase their labor productivity 50 times by dividing the production process into 18 operations and assigning each worker to only two or three operations. Today, every commodity and service are the result of division of labor among thousands of specialized workers around the world. I can purchase a variety of products and services at low prices due to the productivity gained from specialization. Therefore, specialization is a key foundation for the material affluence we are enjoying.

Anecdotes abound on the impacts of information technology (IT) on specialization. A well-known example wherein IT influenced the task scope of workers is IBM Credit Corporation (Hammer 2009). The company reengineered its credit issuance process with the help of IT, which replaced specialists with generalists who can conduct multiple tasks (e.g., checking creditworthiness, determining interest rates, preparing loan agreements) and increase the overall process efficiency. Another case in point is Uber. The Uber platform provides several convenient features such as matching with customer routes, flexible fare systems, and the use of mobile devices and a global positioning system (GPS), thereby allowing Uber drivers to be specialized in non-automatable complex tasks, namely, driving a car and interacting with customers. Although these cases and other anecdotes indicate that IT can fundamentally change the task allocations between machines and humans, I do not have a comprehensive understanding of whether or how IT influences worker specialization. Considering the importance of specialization as a micro-foundation of productivity growth, it is imperative to investigate the impact of IT on worker specialization.

However, prior literature has been silent regarding how information technology (IT) affects specialization. In fact, the relationship between IT and specialization is theoretically unclear. On one hand, IT can decrease specialization. By enhancing the information processing capabilities of organizations, IT has been replacing simple, repetitive tasks such as assembly or calculation through automation and offshoring (Acemoglu and Autor 2011; Acemoglu and Restrepo 2018; Autor et al. 2003; Brynjolfsson and McAfee 2012). Given that such routine tasks are designed to increase unskilled workers' productivity by making them specialists based on Taylorism and Fordism (Drucker 1999; Mintzberg 1979), the decrease in routine tasks due to IT might have decreased workers' degree of specialization (Deming 2017; Lindbeck and Snower 2000). Indeed, Drucker (1999) predicted that technological advances would lead to the emergence of generalists or "technologists" who flexibly perform a variety of tasks including technical, cognitive, and manual tasks.

On the other hand, prior studies maintain that IT may foster worker specialization by reducing coordination costs incurred by workers when interacting with other workers (Gurbaxani and Whang 1991; Malone and Crowston 1994; Malone 2011; Mintzberg 1979). Given that such coordination costs among workers constrain the extent of specialization (Becker and Murphy 1992), IT can increase worker specialization by reducing coordination costs. Also, empirical evidence suggests that IT may be associated with an increasing number of routine cognitive occupations (Hershbein and Kahn 2018), and that IT use may be associated with specialization in managerial occupations (Pinsonneault and Rivard 1998). These studies suggest that IT can increase worker specialization by enabling a more flexible and integrative division of labor between machines and workers, as well as among workers.

To reconcile these countervailing views concerning the impact of IT on specialization, we develop a theoretical framework to explain how a worker's specialization is determined by the coordination cost structure of occupations and other occupational characteristics affecting coordination costs, such as urban agglomeration and required cognitive skill levels, based on the relevant literature on specialization (Becker and Murphy 1992; Mintzberg 1979) and the transaction cost economics (TCE) perspective (Williamson 1981). Then, I explain how IT can affect specialization by drawing on the automation and offshoring literatures in IS and economics (Acemoglu and Restrepo 2018; Autor et al. 2003; Bresnahan et al. 2002; Mani et al. 2014; Mithas and Whitaker 2007). Further, I extend our arguments to explain how IT can increase specialization to a greater extent for occupations requiring higher levels of cognitive skills (Autor et al. 2003; Bresnahan et al. 2002; Spitz-Oener 2006) and occupations that are more likely to be located in urban areas (Autor 2019). Specifically, I address the following research questions: *(1) Is IT associated with an increase in an individual worker's specialization?; and (2) Which occupational characteristics moderate the relationship between IT and specialization?*

To validate our arguments, I employ an occupation-year panel analysis based on data from the Occupational Network (O*NET) database of the U.S. Department of Labor/Employment and Training Administration (USDOL/ETA) and the Occupational Employment Statistics (OES) program of the U.S. Bureau of Labor Statistics (BLS) on 656 occupations during the period 2003-2018; the data contain rich information about each occupation's task composition and computer use. I find that on average, IT use has a significant positive impact on specialization, implying that IT enables workers to be more (rather than less) specialized. I also find significant heterogeneity in the impact of IT across occupations. Our results suggest that the impact of IT on specialization is greater for occupations requiring higher cognitive skills and for occupations located in cities. Moreover, an additional analysis reveals a positive association between our specialization measure and wages, suggesting that IT increases wages through specialization. I demonstrate the robustness of our findings by using an alternative measure of specialization, IT variables, and a matching technique.

2. Literature Review

The literature directly related to our study examines how IT has changed the division of labor between humans and machines, as well as among human workers. In particular, recent studies have used a task-based approach that focuses on the impact of IT at the task level. The findings of these studies show that IT has changed task allocation via two mechanisms: automation and offshoring (Acemoglu and Restrepo 2018; Autor et al. 2003; Bresnahan et al. 2002; Mani et al. 2014; Mithas and Whitaker 2007; Tambe and Hitt 2012). IT can automate tasks by enabling machines to perform simple repetitive tasks, of which the processes are explicitly specified (Autor et al. 2003). Given that the processes for carrying out such tasks can be explicitly specified, they can be programmed, thereby allowing machines to perform such routine tasks without human intervention. Indeed, due to the improvement and adoption of automation technologies, there has been a significant decrease in routine tasks and an increase in the demand for non-routine tasks (Autor et al. 2003; Spitz-Oener 2006). Accordingly, there has been a decrease in the number of occupations specializing in routine tasks (e.g., operators, office clerks) and an increase in the number of occupations specializing in non-automatable, complex tasks (e.g., managers, professionals) (Acemoglu and Restrepo 2018; Autor et al. 2003; Spitz-Oener 2006).

In addition, by increasing the organizational information processing capability, IT can reduce costs for coordinating the interactions among heterogenous agents (including costs for monitoring, contracting, and communication) within and across firm boundaries (Brynjolfsson et al. 1994a; Gurbaxani and Whang 1991; Im et al. 2013). Based on the coordination capabilities of IT, some studies have examined whether offshoring substitutes for simple tasks (Acemoglu and Autor 2011; Blinder 2009; Mithas and Whitaker 2007; Tambe and Hitt 2012). While IT-enabled offshoring allows firms to outsource their tasks across geographical and cultural boundaries, previous research has found that it is not effective for certain types of tasks. Because IT cannot directly process tacit knowledge (which is difficult to express in a symbolic system), IT is more likely to facilitate the offshoring of simple tasks that do not require such tacit knowledge (Mithas and Whitaker 2007). In addition, tasks requiring complex physical movement are not effectively coordinated through IT; therefore, tasks requiring workers' physical presence are not likely to be offshored (Mithas and Whitaker 2007).

These studies provide valuable insights regarding how IT has changed labor markets via automation and offshoring and discuss implications for certain tasks and occupations affected by IT. Specifically, their findings suggest that automation and offshoring enabled by IT have led to a decreasing number of middle-skilled occupations specialized in simple routine tasks that are automatable and offshorable, a phenomenon known as job polarization. However, many questions remain unanswered regarding how IT has affected the nature of work by changing the division-of-labor system between humans and machines, as well as between domestic and foreign workers. One important aspect regarding the nature of work potentially affected by IT is workers' degree of specialization, given that specialization is the result of task allocation and coordination on which IT has a significant bearing.

Prior research has been equivocal regarding the impact of IT on worker specialization. Several studies suggest that IT may decrease worker specialization by replacing simple routine tasks and complementing complex tasks (Acemoglu and Restrepo 2018; Autor et al. 2003; Deming 2017; Drucker 1999; Lindbeck and Snower 2000; Spitz-Oener 2006). In contrast, several researchers have presented opposite views (Malone 2011; Mintzberg 1979). Notably, Mintzberg (1979) suggests that technology-enabled automation can increase the specialization of factory operators by compelling them to concentrate on their non-automated tasks. Indeed, he argues that highly specialized workers would work in an agile organizational structure, or adhocracy in his terminology, enabled by automation and outsourcing (Mintzberg 1981). Malone (2011) also suggests that digital labor platforms might lead to hyperspecialization in professional workers by improving their coordination. Further, a few IS scholars have found that IT increases specialization in managerial occupations by allowing them to focus on the tasks that they perceive as important (Pinsonneault and Rivard 1998).

Despite these conflicting views regarding IT's impact on specialization, there has been scant research on this topic. Some studies have examined the productivity effect of multitasking (Aral et al. 2012; Goes et al. 2018), while other studies have found that social skills increase specialization and productivity (Deming 2017), based on the assumption that technical advances decreases worker specialization. However, these studies did not directly examine the relationship between IT and worker specialization. In this paper, I aim to fill this gap in the literature.

3. Theoretical Background

3.1. Specialization

A specialist is someone who knows more about less (Becker and Murphy 1992; Mintzberg 1979). The superior performance of specialists comes at the expense of narrowness in their task scope. One extreme example of a specialist is factory operators. They are assigned to only one activity such as hammering, and thus are extremely specialized in that activity. Another example is a radiologist who is specialized in using medical imaging techniques for diagnosis. Even though radiologists have a richer configuration of activities compared to factory workers, their tasks are centered on creating and interpreting medical images; therefore, radiologists are moderately specialized. I conceptualize specialization as the degree of concentration involving the distribution of a worker's working hours over a variety of tasks allocated to the worker, and investigate whether and how IT impacts the degree of specialization.

Our framework on specialization is based on the TCE perspective, which has been used to explain how firms' boundary decisions (i.e., make vs. buy) are made (Williamson 1981). According to TCE, a firm's boundary is determined by the trade-off between the internal coordination costs for managing interdependencies within a firm, external coordination costs for managing interactions between the firm and external suppliers, and production costs. Firms' make-or-buy decisions are made based on the relative size of these costs. When the sum of the production costs of the market (which is assumed to have advantages due to its large scale of production) and the external coordination costs is lower than the sum of the internal production costs and the internal coordination costs, firms choose markets over hierarchies (i.e., internal production). I adapt TCE to our context and reconceptualize coordination costs, a firm-level concept, at the individual worker level. Specifically, in this study, internal coordination costs refer to the costs incurred for coordinating the tasks of a single worker, and external coordination costs are incurred for the interactions among individual workers within or across organizational boundaries.

Specialization leads to a reduction in individual workers' internal coordination and production costs, and an increase in external coordination costs among workers such as the monitoring cost, contract cost, communication cost, and transportation costs (Becker and Murphy 1992; Mintzberg 1979). Therefore, the optimal degree of specialization is determined by the trade-off among these costs. First, specialization reduces the internal coordination costs for performing diverse tasks (Mintzberg 1979). Given that different tasks require different tools and locations, workers must switch their tools and locations to perform diverse tasks. In addition, because some tasks are interdependent such that the outputs of some tasks are used as an intermediate input for other tasks (Malone and Crowston 1994), a change in a preceding task requires changes in the subsequent tasks, thus increasing the need for coordination. Because specialization reduces the variety of tasks in a worker's task bundle, the worker has less of a need to coordinate across his/her tasks. Therefore, specialization makes a worker's job simpler and reduces his/her internal coordination costs. In addition, specialization reduces production costs, as it allows workers to repeat similar tasks. As workers concentrate their working hours on a smaller number of activities, they can repeat those tasks more, thereby accumulating more task-specific experience and knowledge. This accumulated knowledge in turn helps workers decrease production costs (Becker and Murphy 1992; Gibbons and Waldman 2004).

However, these benefits from specialization come at the expense of increased external coordination costs. First, specialization increases the degree of interdependency among workers. With increasing specialization, each worker takes charge of a narrower part of the entire production process. Consequently, their outputs are increasingly used as intermediate inputs for other workers' tasks; in addition, these workers need more intermediate inputs produced by other workers. Hence, the interactions among workers increase, resulting in increased external coordination costs (Becker and Murphy 1992). Moreover, as the degree of specialization increases, the number of workers in a division-of-labor system tends to increase because these workers perform smaller subtasks, which increases the size of the "team" (Becker and Murphy 1992).

Due to the co-existence of the aforementioned benefits and costs, the degree of a worker's specialization cannot go beyond the point where the benefits are the same as the external coordination costs. In other words, the external coordination costs of an individual worker are a major constraint in the degree of his/her specialization (Becker and Murphy 1992). According to TCE, the optimal firm boundary contains core functions for which the firm has production cost advantages over markets, and additional processes involved in production for which outsourcing does not make economic sense (i.e., the external coordination costs are larger than the sum of the internal coordination and the difference between external and internal production costs) (Williamson 1981). Similarly, a worker's optimal task bundle, which is determined by the aforementioned trade-off between individual-level coordination and production costs, contains core tasks for which the worker has a comparative advantage in production costs over other workers, and non-core tasks that cannot be outsourced due to large external coordination costs. As such, a worker's degree of specialization is determined by the scope of his/her task bundle.

3.2. Task Complexity and Specialization

I argue that a major factor affecting the degree of specialization in an occupation is the complexity of the tasks performed by the occupation. While a number of definitions of task complexity exist (Campbell 1988; Liu and Li 2012), I refer to complex tasks as tasks performed by high-skilled workers such as managerial or analytical tasks, following the RBTC literature (Acemoglu and Autor 2011; Acemoglu and Restrepo 2018) and Mintzberg (1979). This definition stems from a task-human interactional viewpoint (Liu and Li 2012; March and Simon 1958), which defines task complexity in terms of the relative capabilities of the task-doers: tasks are more or less complex relative to the capabilities of the individual performing the task. In this view, there are many objective aspects of tasks that increase task complexity such as uncertainty in the process or outcomes or the number of subtasks to coordinate internally (March and Simon 1958). In addition, task complexity is affected by certain worker characteristics such as prior knowledge and experience because these characteristics enhance worker's capability to perform their tasks.

According to TCE (Williamson 1981), there are particular aspects of transactions that increase external coordination costs. Specifically, information asymmetry (between contracting parties) and the uncertainty of a transaction increase a firm's external coordination costs because they make it difficult to predict the transaction outcomes, entailing opportunistic behaviors of the economic agents. Therefore, firms resort to internal production when procuring products from the market creates information asymmetry or uncertainty. Similarly, Mintzberg (1979) argues that occupations performing complex tasks (such as managers or professionals) attain relatively low specialization compared to occupations with simpler tasks such as operators and office clerks. Because it is difficult to monitor and coordinate complex tasks, workers must perform such tasks by themselves to avoid high external coordination costs. Therefore, task complexity, which creates uncertainty and information asymmetry, decreases worker specialization. For example, medical doctors can diagnose a disease by analyzing various medical data. Although the analysis and diagnosis can be divided and done separately, the communication process is complex because synthesizing such data requires complex cognitive processes; therefore, doctors must perform those various tasks by themselves. In this sense, a complex task is less divisible and thus consists of many subtasks that need to be performed by one person due to high external coordination costs when they are allocated to multiple workers. Consequently, occupations performing more complex tasks are likely to have lower degrees of specialization.

4. Hypotheses Development

4.1.IT and Specialization

Theoretically, it is not clear whether IT is associated with an increase or decrease in the degree of worker specialization. On one hand, IT can decrease the degree of specialization by decreasing highly specialized occupations and increasing less specialized occupations. Given that IT can automate or offshore simple, repetitive tasks of which the processes can be explicitly specified, IT reduces such routine tasks (Acemoglu and Autor 2011; Autor et al. 2003; Mithas and Whitaker 2007). As those tasks are designed to reduce external coordination costs by specifying rules (Mintzberg 1979), they have low information asymmetry and uncertainty among co-workers performing those tasks. Therefore, such automatable and offshorable tasks incur low external coordination costs, and workers specialized in such simple tasks are highly specialized (Drucker 1999; Mintzberg 1979). As IT substitutes for automatable and offshorable tasks, the number of such specialized occupations decreases, thereby decreasing the overall degree of worker specialization

In addition, IT can create new tasks such as developing computer programs for analytics or designing IT-based business models that require a great deal of interaction with computerized devices (Acemoglu and Autor 2011; Autor et al. 2003). These tasks are typically complex due to the uncertainty stemming from their novelty; therefore, they cannot be easily replaced by IT (Acemoglu and Restrepo 2018) and thus incur high external coordination costs. As a result, by adding such new complex tasks with high external coordination costs in workers' task bundles, IT can decrease the degree of their specialization. As the number of less specialized occupations performing complex tasks—non-routine and high-skilled occupations (Acemoglu and Autor 2011; Autor et al. 2003)—increases, the average degree of worker specialization decreases. In sum, by replacing simple, routine tasks and creating complex, non-routine tasks (Acemoglu and Autor 2011; Acemoglu and Restrepo 2018; Autor et al. 2003), IT can decrease worker specialization on average (Aral et al. 2012; Deming 2017; Drucker 1999; Lindbeck and Snower 2000).

One example of such change is office automation. As many office automation tools such as Microsoft Excel, Words, and PowerPoints are adopted in the office, they automate many time-consuming repetitive tasks, such as text editing or calculation. While these software tools replace highly specialized typists and human computers, they also increase the amounts of non-replaceable tasks such as writing, data analysis, and presentation as they can easily conduct such tasks using labor-saving features of office automation tools (Acemoglu and Autor 2011; Autor et al. 2003). As these tasks are more complex compared to typing or simple calculation, these new tasks consist of highly dependent subtasks that are not divisible such as modelling, designing slides and creating ideas. Therefore, using such office automation tools increases the complexity of tasks, making workers less specialized.

On the other hand, IT can increase the degree of specialization involving occupations that perform complex tasks by reducing the associated external coordination costs. Although IT cannot automate or offshore such complex tasks (Acemoglu and Autor 2011; Acemoglu and Restrepo 2018; Autor et al. 2003), IT can reduce firms' external coordination costs by decreasing the communication costs for exchanging information to coordinate the tasks (Bresnahan et al. 2002; Gurbaxani and Whang 1991). Given that high external coordination costs come from the information asymmetry and uncertainty caused by task complexity, IT can lower such costs by facilitating communication and information sharing among workers. IT also allows workers to access massive amounts of information from both internal and external sources, which can reduce uncertainty. In this sense, IT enables workers to coordinate and carry out complex, interdependent tasks more efficiently. As a result, IT allows workers to incur lower external coordination costs for complex tasks and makes such tasks more divisible so that the subtasks can be allocated to and carried out by multiple workers. Together, this can result in an increased degree of specialization for non-routine, high-skilled occupations performing complex tasks such as managers (Pinsonneault and Rivard 1998) and professionals (Malone 2011).

For example, workers can communicate more efficiently with other co-workers by using many different types of communication tools such as e-mail, and mobile messenger. Such efficient communication tools allow workers to outsource their marginal tasks to specialists who are the most suitable for the tasks. They can constantly exchange information to coordinate their work across the geographical and organizational boundaries. Through the expanded outsourcing practices, task allocation becomes more efficient such that workers are allocated to the tasks in which they are specialized, and they become more specialized as they are increasingly allocated to the tasks they are specialized in.

As discussed above, due to the countervailing mechanisms through which IT can affect worker specialization, the net impact of IT is an empirical question. As a working hypothesis, I propose the following:

H1: IT is positively associated with worker specialization.

4.2.The Moderating Role of Cognitive Skills

I argue that cognitive skills positively moderate IT's impact on specialization. Cognitive skills refer to basic learning skills used to think, read, learn, remember, and reason, all of which allow workers to obtain and process new information efficiently. In the economics literature, cognitive skills are an important part of human capital that can be acquired from schooling. Prior studies have found that these cognitive skills, measured by test scores (Deming 2017; Hanushek et al. 2017; Hanushek and Woessmann 2008), are important for workers' economic success, as well as for new technology adaptation by allowing workers to process new information more effectively.

I argue that cognitive skills help workers become more specialized by reducing external coordination costs arising from complex tasks increased by IT. Workers with high cognitive skills can coordinate complex tasks created by IT more easily, as they can better understand information when dealing with uncertainty (Bresnahan et al. 2002, Bartel and Lichtenberg 1987). For example, Bartel and Lichtenberg (1987) suggest that highly educated workers can better adapt to new technologies because they can better understand these new technologies and the resulting changes. While new complex tasks created by IT increase uncertainty and information asymmetry among workers (which makes cross-worker coordination difficult), workers with high cognitive skills can reduce such uncertainty and information asymmetry by processing relevant information more effectively. For example, Pinsonneault and Rivard (1998) discuss cases involving middle managers, where IT usage by middle managers (with high cognitive skills) is positively associated with information-related activities such as monitoring operations and diffusing information to colleagues. As a result, those managers can focus on specific tasks that are perceived as critical to their managerial roles. To the extent that cognitive skills help workers process information more efficiently, cognitive skills would amplify specialization driven by IT usage. Hence, I propose the following hypothesis:

H2: Cognitive skills positively moderate the impact of IT on specialization.

4.3. The Moderating Role of Urban Agglomeration

I argue that the degree of urban agglomeration in an occupation (the extent to which an occupation is located in urban areas) influences the extent to which IT affects specialization. The literature on the economics of agglomeration suggests that workers residing in cities are more productive and earn higher wages, especially for high-skilled workers in managerial and professional occupations (Frank et al. 2018; Glaeser and Mare 2001; Glaeser and Resseger 2010). While there are many theoretical explanations on why an urban wage premium exists (Duranton and Puga 2004), one explanation is that cities provide physical proximity, which reduces external coordination costs (Becker and Murphy 1992). When workers performing interdependent tasks are located close to one another, they can reduce transportation costs and increase the frequency of face-to-face meetings, which are the most effective form of communication (Storper and Venables 2004). In addition, based on the shared experience, they can build shared knowledge (Espinosa et al. 2004; Rico et al. 2008), which helps reduce information asymmetry among co-workers. This implicit coordination mechanism facilitates the division of labor for complex tasks. Because physical proximity reduces the interaction costs among workers, cities can form large, efficient division-of-labor systems where the workers can be highly specialized and more productive, resulting in the wage premium.

Technological advances have pushed the economics of agglomeration further (Autor 2019; Florida 2017; Lin 2011; Mithas and Whitaker 2007). As IT increases the proportion of complex tasks in workers' task bundles, workers need greater physical proximity to reduce the external coordination costs involved in performing complex tasks because collocation facilitates information/knowledge spillover by allowing workers to meet and share knowledge more easily (Becker and Murphy 1992; Duranton and Puga 2004). Given that cities provide workers with greater physical proximity based on the high population density, urban agglomeration can positively moderate the impact of IT on specialization by reducing the external coordination costs arising from complex tasks.

A case in point is tech entrepreneurs who start their businesses based on new technologies (e.g., advanced analytics) (Helsley and Strange 2002). Innovative tech startups face high uncertainty from their complex, new tasks such as designing IT platforms or operating viral marketing, and thus require intensive coordination among their workers. The close physical proximity provided by cities allows tech entrepreneurs to reduce high external coordination costs incurred by their workers, resulting in efficient collaboration and increased specialization. This explains why most innovative businesses based on new advanced IT are clustered in urban areas (e.g., Silicon Valley), and why such new businesses create new tasks and highly specialized professionals in cities (Acemoglu and Restrepo 2018; Autor et al. 2003; Frank et al. 2018; Lin 2011). Based on the discussion above, I propose the following hypothesis:

H3: *The degree of urban agglomeration positively moderates the impact of IT on specialization.*

5. Research Method

5.1. Data

I test our hypotheses using data from the Occupational Network (O*NET) database of the U.S. Department of Labor/Employment and Training Administration (USDOL/ETA) and the Occupational Employment Statistics (OES) program of the U.S. Bureau of Labor Statistics (BLS) for the period 2003-2018. A total of 812 occupations were identified from the O*NET database using the 2010 standard occupational classification (SOC). Our variables—Specialization, IT, Cognitive Skill, and Occupational Group—were derived from the same database. O*NET is one of the few reliable databases that provide rich information about the task composition of occupations for a sufficiently long period; indeed, it has been widely used in prior research in both economics and IS (Autor and Price 2013, Tambe and Hitt 2012). The O*NET database collects occupational data using surveys of incumbent workers and opinions of their occupational experts.

Because the O*NET database updates approximately 100 occupations annually, several occupations are not updated each year. For example, the occupation of Chief Executive Officer has been updated three times in 2007, 2013, and 2014. In the original database, missing values are imputed by the Last Observation Carry Forward (LOCF) method, which imputes the missing data using the most recent observations. Although LOCF is widely used in many clinical trials, there has been the criticism that LOCF may result in biased estimates (NRC 2010). Therefore, I use another approach, namely, complete-case analysis in which missing cases are discarded and standard analysis methods are applied to complete cases only. This complete-case analysis is valid when the missing data are missing completely at random (MCAR), that is, when the selection of missing data is probabilistically independent of the focal variables used in the analysis. Given that the incomplete update scheme of O*NET is not directly related to the variables in this research, it is plausible to assume that our data satisfy the MCAR condition. I estimate linear regression models with time-fixed effects to test the research hypotheses. The heterogeneity across occupations on specialization due to their task complexity is controlled by occupational group dummy variables.

In addition, I use data from OES for occupation-time specific national employment, occupation-time specific Metropolitan Statistical Area (MSA) employment, and annual wages. I employ the estimates of the occupation-time specific employment number at the national level to be consistent with the O*NET database. I use them as the weight for each occupation in the analysis to control for the influence of occupation size, which is consistent with previous research (Autor et al. 2003, Spitz-Oenor 2006). I use occupation-time specific MSA employment data to derive the urban agglomeration variable. Annual wage data are used for one of our additional analyses. Our final samples consist of 1,982 occupation-year observations from 782 occupations for the period 2003-2018.

5.2.Variables

Our dependent variable, Specialization, is measured by the Gini coefficient of the "importance" measures associated with 41 work activity descriptors. The Gini coefficient is a popular measure involving the disparity type of diversity used by previous studies (Harrison and Klein 2007). It measures how unevenly a measure (such as income) is distributed over a group of people or items. The Gini coefficient is defined based on the Lorenz curve, which represents percentiles of the population against the cumulative income of people at or below that percentile. If income is perfectly evenly distributed, the Lorenz curve becomes a 45-degree line, which represents a perfectly equal distribution of the score. The Gini coefficient is calculated as the ratio of the area lying between the 45-degree line and the Lorenz curve over the total area under the 45-degree line; therefore, the Gini coefficient captures the degree of inequality. Under a perfectly even distribution, the Gini coefficient becomes 0, whereas it assumes the value of 1 if income is perfectly unevenly distributed.

In this research, I construct a Gini coefficient to measure how unevenly the importance measures are distributed over 41 work activities. The "importance" indicates the degree of importance regarding a certain task on the job performance within a given occupation. Because there is no direct measure of the amount of time spent for each type of task, I use the importance measure as a proxy for the amount of time spent. Every occupation has importance scores for all 41 general activities in the database. If an occupation does not perform a certain activity, the importance score for that activity would be zero; otherwise, it would be larger than zero. A high Gini coefficient indicates that the distribution of importance is uneven, implying that some tasks are more important than the remaining tasks. On the other hand, a low Gini value means that the importance of all tasks is similar to one another. Therefore, I interpret a higher (lower) Gini value as implying that the workers in a given occupation are more (less) specialized.

Our main independent variable, IT, is a "level" measure of "Interacting with Computer Work Activity" descriptor rather than an "importance" measure used in calculating the specialization measure. It represents the required skill level for using computers and computerized systems (including hardware and software) to program, write software, set up functions, enter data, or process information. Basically, it reflects the extent to which an occupation uses IT tools in its work. Although O*NET provides an importance measure for the "Interacting with Computer Work Activity" descriptor, the importance measure is used in calculating the specialization. To avoid using the same importance measure in the dependent and independent variables, I use the level measure. [1]

I include four indicator variables to control for heterogeneity across occupations. Based on Mintzberg's (1979) categorization of occupations with varying degrees of specialization (see Appendix 2), I suggest five occupational groups, a *managerial group* performing managerial tasks; a *professional group* specialized in analytical tasks; *office clerks* who are specialized in routine cognitive tasks; *operators* performing simple routine manual tasks in factories; and non-routine manual workers, capturing all other types of manual occupations performing complex manual tasks (e.g., construction workers). I include four dummy variables: a professional group, office clerks, operators, and non-routine manual workers; the managerial group is the baseline occupational group. These occupational groups are operationalized based on the "major group" in the SOC system.[2]

To test our second hypothesis, I develop a cognitive skill variable that captures the abilities to learn (e.g., reading, listening, critical thinking, and writing). This variable is operationalized as the average of 10 skills in the Basic skills category in the skills descriptor of O*NET. The basic skills in O*NET are defined as the skills used for the rapid acquisition of knowledge. To test our third hypothesis, I measure the degree of urban agglomeration of an occupation by the ratio of employment of the occupation in MSA to the national employment of the occupation using data from the OES database. The greater the proportion of an occupation hired in urban areas, the higher the ratio is. Variable definitions are provided in Table 1.

Table 1. Variable Definition

[1] In addition, I also used the importance score of "Interacting with computer" work activity descriptor in O*NET database as an alternative measure of IT usage, and obtained qualitatively similar results.
[2] The occupations in the SOC system are classified at four levels of aggregation: major group, minor group, broad occupation, and detailed occupation. There are 23 major groups in the SOC system; we aggregated those 23 major groups into our five occupational groups. The complete lists are in Appendix 1.

Variable	Notation	Definition	Operationalization
Specialization	SP_{it}	The degree of concentration of the distribution of a worker's working hours over a variety of tasks allocated to the worker	The Gini coefficient of the importance scores of 41 Work Activity Descriptors in the O*NET database. The importance measure of the work activity is defined as the importance of a certain task on the job performance. The range is 0 – 5.
IT	IT_{it}	The extent to which an occupation uses IT tools in its work	The level score of "Interacting with Computer Work Activity" in the Work Activity Descriptor in O*NET database. The range is 0 – 7. The level measure is defined as the degree to which the descriptor is required to perform the occupation.
Cognitive skill	Cog_{it}	The abilities to learn (e.g., reading, listening, critical thinking, and writing)	The mean of Basic skills in the skills descriptor. The range is 0 – 5. Basic skills are defined as Developed capacities that facilitate learning or the more rapid acquisition of knowledge.
Urban Agglomeration	Urb_{it}	The proportion of an occupation hired in urban areas	The proportion of employment of the occupation in MSAs over the national employment of the occupation. The range is 0 – 1. Urban Agglomeration is defined by how the occupations are clustered in urban areas.
Professional Group*	$Prof_{it}$	The occupations that perform complex cognitive tasks for administrative functions such as designing an organizational structure, performing legal tasks, and developing a technical system	A binary variable indicating whether an occupation belongs to a professional group (1) or not (0)
Office Clerk Group*	Off_i	The occupations that perform basic work related directly to production	A binary variable indicating whether an occupation belongs to office clerk group (1) or not (0)
Operator Group*	$Oper_i$	The occupations that perform simple cognitive tasks for managers and professionals	A binary variable indicating whether an occupation belongs to the operator group (1) or not (0)

Non-routine Manual Worker*	Man_i	The occupations that work in an uncontrolled environment outside a large organization.	A binary variable indicating whether an occupation belongs to the non-routine manual worker group (1) or not (0)

*Note: The list of occupations in each category is provided in Appendix 1.

5.3. Descriptive Statistics

Table 2 presents the descriptive statistics for our variables. Because the occupational group variables are binary, the descriptive statistics are not available for them. Note that the descriptive statistics are weighted by the employment number to account for the effect of occupation size.

Table 2. Descriptive Statistics

Variable	Mean	S.D.	Min	Max	1	2	3	4
1. Specialization	0.152	0.034	0.058	0.296	1.00			
2. IT	2.720	1.196	0.030	6.305	0.13***	1.00		
3. Cognitive Skill	3.143	0.455	1.665	4.576	0.14***	0.56***	1.00	
4. Urban Agglomeration	0.827	0.107	0.004	0.969	0.06***	0.24***	-0.01	1.00

5.4.Empirical Specification

To test our hypotheses, I use the following the time-fixed effect model specification:

$$SP_{it} = IT_{it-1} + Cog_{it} + Urb_{it} + Prof_{it} + Off_{it} + Oper_{it} + Man_{it} + IT_{it-1} \times Cog_{it} + IT_{it-1} \times Urb_{it} + D_t + \varepsilon_{it}$$

where *i* indicates the occupation, and *t* denotes the year. I lag our main independent variable, IT, by one year to address the simultaneity issue and account for the lagged effect of IT. The term D_t captures the time-specific effect, and ϵ_{it} is an error term assumed to be normally distributed with zero mean and constant variance. I first estimate the model without the interaction term to examine the unconditional effect of IT on specialization. Then, I re-estimate the model with the interaction terms to examine the differential effects of IT according to the cognitive skill level and the degree of urban agglomeration.

6. Results

6.1. Impact of IT on Specialization

I estimate our model using ordinary least square (OLS) to test the research hypotheses. Variance inflation factors (VIFs) are lower than 10 for all independent variables, except for the interaction terms (Greene 2003), indicating that multicollinearity is not a concern in the analysis.

The results in Model (2) of Table 3 suggest that the overall effect of IT on specialization is positive ($\beta = 0.006$, $p < 0.01$). A one-unit increase in IT, of which the range is 0-7, is associated with a 0.006-unit increase in worker specialization. Because the average degree of specialization of U.S workers is 0.152, as in Table 1, this corresponds to a 4 % increase compared to the average degree of specialization. The statistically insignificant estimates on cognitive skills ($\beta = -0.007$, $p > 0.10$) and urban agglomeration ($\beta = 0.006$, $p > 0.10$) in Model (2) suggest that cognitive skills and urban agglomeration may not have direct effects on specialization.

The coefficient estimates of the occupational group indicator variables in Model (2) are all significantly positive. Because the manager group is the reference group, the degree of specialization for the manager group is the same as the constant ($\beta = 0.128$, $p < 0.01$). Compared to the managerial group, the other occupational groups are more specialized. The office clerk group is the most specialized because its coefficient is the largest ($\beta = 0.040$, $p < 0.01$). The professional group ($\beta = 0.034$, $p < 0.01$) is the second most specialized, followed by the operator group ($\beta = 0.028$, $p < 0.01$). The non-routine manual worker group is the second least specialized of all occupational groups ($\beta = 0.018$, $p < 0.01$).

6.2.Moderating Effects of Cognitive Skills and Urban Agglomeration

The results of estimating the interaction effects between IT and two occupational characteristics, cognitive skills and urban agglomeration, are presented in Model (3) of Table 3. The coefficient of the interaction term involving IT and cognitive skill is positive and significant ($\beta = 0.009$, $p < 0.01$), indicating that the cognitive skill positively moderates the impact of IT on specialization. The estimated coefficient is 0.009, which means that on average, a one-unit increase in the cognitive skill variable is associated with a 0.009 unit increase in specialization when the IT variable remains the same. Because the average degree of specialization is 0.152 (see Table 1), it corresponds to a 5.9% increase compared to the average degree of specialization.

The coefficient on the interaction term involving IT and urban agglomeration is significantly positive ($\beta = 0.029$, $p < 0.01$), indicating that the degree of urban agglomeration positively moderates the impact of IT on specialization. Because the standard deviation of urban agglomeration is 0.107, the increase by one standard deviation is associated with a 0.003-unit increase in specialization, which is a 2% increase compared to the average degree of specialization.

Table 3. The Impact of IT on Specialization and The Moderating Effects of Cognitive Skills and Urban Agglomeration

Dependent variable	**Specialization**		
Model	**(1)**	**(2)**	**(3)**
IT		0.006 *** (0.001)	-0.048 *** (0.007)
Cognitive Skill	0.000 (0.005)	- 0.007 (0.004)	- 0.019 *** (0.006)
Urban Agglomeration	0.018 ** (0.008)	0.006 (0.008)	-0.050 *** (0.013)
Professional Group	0.037 *** (0.004)	0.034 *** (0.004)	0.032 *** (0.004)

Office Clerk Group	0.042 *** (0.005)	0.040 *** (0.005)	0.044 *** (0.005)
Operator Group	0.027 *** (0.006)	0.028 *** (0.006)	0.027 *** (0.005)
Non-routine Manual Worker Group	0.014 *** (0.005)	0.018 *** (0.005)	0.018 ** (0.005)
IT × Cognitive Skill			0.009 *** (0.002)
IT × Urban Agglomeration			0.029 *** (0.005)
Constant	0.112 *** (0.017)	0.128 *** (0.017)	0.214 *** (0.019)
R-squared	0.271	0.293	0.322
F – Statistics	22.20	24.59	26.10
Observations/ Groups	1991/16	1991/16	1991/16
Notes: *p<0.10, **p<0.05, *** p<0.01; all two-tailed tests. Unstandardized coefficients are reported. Standard errors are in parentheses.			

7. Additional Analysis

7.1.Specialization and Wage

According to prior literature on specialization (Aral et al. 2012; Becker and Murphy 1992; Goes et al. 2018; Kim 1989; Kim and Kim 2014; Narayanan et al. 2009; Wasmer 2006), specialization contributes to productivity, as it allows a worker to accumulate more task-specific human capital. Therefore, to examine the productivity implications of specialization, I investigate the relationship between specialization and annual wages. Given that labor productivity is related to a worker's wage level, I expect that there is a wage premium associated with specialization. To confirm this conjecture, I estimate a time fixed-effect model to examine the relationship between specialization and annual wages with several control variables, including occupational group indicators, IT, cognitive skills, and urban agglomeration. Annual wages are divided by 1,000 to adjust the number of digits and are adjusted based on the Consumer Price Index (CPI) with 2012 as the base year.

As shown in Model (2) of Table 4, specialization is positively associated with annual wages ($\beta = 88.393$, $p < 0.01$). Given that the standard deviation of specialization is 0.034, a one-standard-deviation increase in the degree of specialization is associated with approximately 3,005 US dollars. Compared to the average annual wages in the data, 50,145.62 dollars, a one-standard-deviation increase in the degree of specialization is associated with an approximate 6% increase in annual wages. In Model (2), IT is positively associated with annual wages ($\beta = 3.899$, $p < 0.01$), consistent with the previous findings (Krueger 1993). In addition, the directions of many control variables are consistent with previous literature. For example, Urban Agglomeration is also positively associated with wages ($\beta = 8.389$, $p < 0.01$), which is consistent with empirical studies in regional economics (Glaeser and Mare 2001; Glaeser and Resseger 2010). Cognitive skills are positively associated with annual wages ($\beta = 19.566$, $p < 0.01$), which is consistent with previous literature (Murnane et al. 1995).

Based on the results in Tables 3 and 4, I can conclude that specialization is one of the mediating mechanisms through which IT increases wages. Given that IT increases specialization (see Table 3), a part of the wage premium due to IT is mediated through specialization. I conduct a causal mediation analysis with a non-parametric bootstrap approach (Tingley et al. 2014) and find that the estimated average mediation effect is significantly positive ($\beta = 0.5567$, $p < 0.01$), accounting for 12.5% of the total effect of IT on annual wages.

Table 4. The Impact of Specialization on Annual Wages

Dependent variable	**Annual Wages**	
Model	(1)	(2)
Specialization		88.393 *** (21.528)

IT	4.456 *** (0.780)	3.899 *** (0.790)
Cognitive Skill	18.917 *** (2.470)	19.566 *** (2.455)
Urban Agglomeration	8.959 ** (4.605)	8.389 *** (4.512)
Professional Group	-14.349 *** (3.907)	-17.345 *** (3.946)
Office Clerk Group	-30.535 *** (4.040)	-34.034 *** (4.056)
Operator Group	-23.544 *** (4.191)	-26.031 *** (4.162)
Manual Worker Group	-24.903 *** (3.929)	-26.526 *** (3.907)
Constant	-12.999 *** (10.469)	-24.348 *** (11.132)
R-squared	0.63	0.63
F – Statistics	111.67	104.86
Observations/ Groups	1991/16	1991/16
Notes: *p<0.10, **p<0.05, *** p<0.01; all two-tailed tests. Unstandardized coefficients are reported. Robust standard errors are in parentheses. The unit of annual wages is one thousand dollars.		

7.2.Robustness Checks

7.2.1 Alternative measure of specialization

To check the robustness of our results, I perform various analyses. First, I use an alternative specialization measure based on the coefficient of variation (CV). CV is a statistic defined as the ratio of the standard deviation to the mean of a variable. Similar to the Gini coefficient, CV captures how unevenly the "importance" is distributed over 41 work activity descriptors in an occupation. Because CV is the standard deviation over the mean, a large value indicates a relatively large standard deviation compared to the mean. Given that the standard deviation is a measure of a distribution's dispersion, a large standard deviation would mean that the distribution is largely dispersed or unevenly distributed. Therefore, a large CV involving the distribution of the task importance scores of an occupation means that some tasks are more important than others, which indicates a high degree of specialization for the occupation.

The results based on CV as the specialization measure in Table 5 are qualitatively similar to our main results in Table 3. In particular, the estimate of the IT variable is significantly positive (β = 0.010, p < 0.01) in Model (2), which implies that IT is positively associated with the specialization measure. The relative sizes of the occupational group indicators are also consistent with the main results. Lastly, the moderating effects of cognitive skill (β = 0.018, p < 0.01) and urban agglomeration ((β = 0.051, p < 0.01) are also significantly positive. These consistent results demonstrate the robustness of our main results based on the Gini coefficient as a specialization measure.

Table 5. Estimation Results based on CV as the Measure of Specialization

Dependent variable	Specialization (CV)		
Model	(1)	(2)	(3)
IT		0.010 *** (0.002)	- 0.094 *** (0.015)
Cognitive Skill	- 0.002 (0.008)	- 0.013 (0.008)	- 0.038 *** (0.011)
Urban Agglomeration	0.031 ** (0.013)	0.013 (0.013)	- 0.088 *** (0.022)
Professional Group	0.059 *** (0.007)	0.054 *** (0.007)	0.051 *** (0.006)
Office Clerk Group	0.064 *** (0.009)	0.060 *** (0.009)	0.070 *** (0.008)
Operator Group	0.040 *** (0.010)	0.041 *** (0.010)	0.039 *** (0.009)
Manual Worker Group	- 0.017 ** (0.008)	0.024 *** (0.008)	0.023 *** (0.008)
IT × Cognitive Skill			0.018 *** (0.004)
IT × Urban Agglomeration			0.051 *** (0.009)

Constant	0.207 *** (0.030)	0.234 *** (0.029)	0.398 *** (0.035)
R-squared	0.26	0.28	0.31
F – Statistics	20.04	21.57	24.48
Observations/ Groups	1991/16	1991/16	1991/16
Notes: *p<0.10, **p<0.05, *** p<0.01; all two-tailed test. Unstandardized coefficients are reported. Standard errors are in parentheses.			

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7.2.2 Alternative measures of the IT variable – Automation and E-mail frequency

To check the robustness of our independent variable (IT use), I perform an additional analysis using two alternative measures of IT use: the degree of automation and e-mail usage frequency. I derive both variables from the "Work Context" section in O*NET, which contains information on the physical and social factors influencing the nature of work in an occupation. The degree of automation measures the extent to which an occupation's job is automated. E-mail frequency measures how often an occupation uses e-mail for its job. Because these variables are closely related to computer usage, I believe that these two variables can be used as alternative measures for the IT variable used in our main analysis.

Although the number of observations is different from that in the main analysis due to missing observations for the automation and e-mail frequency variables, as shown in Tables 6 and 7, the results based on these alternative measures are generally consistent with the main results in Table 3. The coefficient on automation ($\beta = 0.012$, $p < 0.01$) in Model (2) of Table 6 indicates that automation is positively associated with the degree of specialization. The interaction term involving automation and urban agglomeration in Model (3) is also significantly positive ($\beta = 0.049$, $p < 0.01$), consistent with the main analysis, although the interaction term between the independent variables with cognitive skill in Model (3) is positive but statistically insignificant ($\beta = 0.004$, $p > 0.10$).

Table 6. The Impact of Automation on Specialization			
Dependent variable	Specialization		
Model	(1)	(2)	(3)
Automation		0.012 *** (0.002)	- 0.039 ** (0.017)
Cognitive Skill	0.000 (0.005)	- 0.001 *** (0.004)	- 0.008 (0.012)
Urban Agglomeration	0.018 ** (0.007)	0.013 * (0.008)	- 0.091 *** (0.026)
Professional Group	0.037 *** (0.004)	0.038 *** (0.004)	0.037 *** (0.004)
Office Clerk Group	0.045 *** (0.005)	0.042 *** (0.005)	0.043 *** (0.005)
Operator Group	0.028 *** (0.006)	0.023 *** (0.006)	0.027 *** (0.006)
Non-Routine Manual Worker Group	0.015 (0.005)	0.018 *** (0.004)	0.019 ** (0.005)
Auto × Cognitive Skill			0.004 (0.005)
Auto × Urban Agglomeration			0.049 *** (0.011)
Constant	0.108 *** (0.18)	0.087 *** (0.018)	0.197 *** (0.039)
R-squared	0.28	0.31	0.32
F – Statistics	23.63	27.61	23.86
Observations/ Groups	1940/15	1940/15	1940/15

Notes: *p<0.10, **p<0.05, *** p<0.01; all two-tailed tests. Unstandardized coefficients are reported. Standard errors are in parentheses.

In Table 7, the coefficient on e-mail frequency ($\beta = 0.012$, $p < 0.01$) in Model (2) is significantly positive. In addition, the two interaction terms involving cognitive skill ($\beta = 0.011$, p < 0.01) in Model (3) and urban agglomeration ($\beta = 0.031$, $p < 0.01$) are positive and significant as well, thereby corroborating the main findings.

Table 7. The Impact of E-mail on Specialization

Dependent variable	Specialization		
Model	(1)	(2)	(3)
E-mail		0.012 *** (0.002)	- 0.050 *** (0.010)
Cognitive Skill	0.009 (0.007)	- 0.014 ** (0.006)	- 0.044 *** (0.011)
Urban Agglomeration	0.028 ** (0.011)	0.012 (0.010)	-0.090 *** (0.030)
Professional Group	0.033 *** (0.005)	0.032 *** (0.005)	0.031 *** (0.004)
Office Clerk Group	0.046 *** (0.006)	0.042 *** (0.006)	0.046 *** (0.006)
Operator Group	0.025 *** (0.008)	0.036 *** (0.008)	0.029 *** (0.008)
Manual Worker Group	0.017 *** (0.006)	0.029 *** (0.006)	0.029 *** (0.006)
E-mail × Cognitive Skill			0.011 *** (0.003)
E-mail × Urban Agglomeration			0.031 *** (0.008)
Constant	0.068 *** (0.025)	0.111 *** (0.022)	0.285*** (0.035)
R-squared	0.26	0.32	0.36
F – Statistics	16.31	22.96	23.57
Observations/ Groups	1124/12	1124/12	1124/12

Notes: *p<0.10, **p<0.05, *** p<0.01; all two-tailed tests. Unstandardized coefficients are reported. Standard errors are in parentheses.

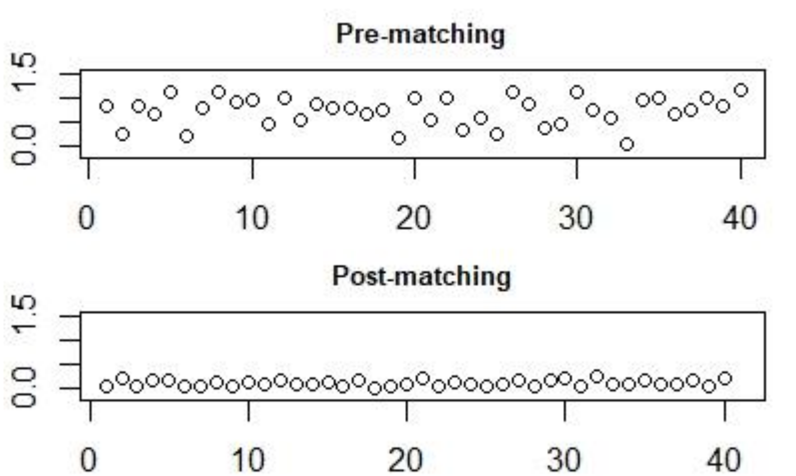
7.2.3 Matching Analysis

I employ a matching approach to address the endogeneity concern that both IT usage and the degree of specialization in an occupation are affected simultaneously by the characteristics of the tasks performed by the occupation. Given that IT use is significantly associated with occupational task content (Autor et al. 2003, Spitz-Oenor 2006), I perform the matching based on 41 types of work activities from the O*NET database. First, I calculate the median value of the IT variable across all occupations and define IT- intensive (non-IT-intensive) occupations as those wherein the IT variable in the previous period is above (below) the median value. Then, I perform matching by using the values of the work activity descriptors in the previous period as the pre-treatment matching values. I use all the work activity variables for matching, excluding the IT variable because it is used to define IT-intensive and non-IT- intensive occupations. This results in pairs of observations (one in the IT-intensive group and the other in the non-IT-intensive group for each pair) with similar task content other than IT intensity.

In terms of the matching algorithm, I employ a genetic matching technique that uses optimally weighted Mahalanobis distance to match the treated and control groups. It is implemented by the "Matchby" command in the "Match" package of the R program (Sekhon 2011). Because the matching is based on 41 work activity variables in our study, the genetic matching technique outperforms other popular multivariate matching techniques such as propensity score matching (PSM) or Mahalanobis distance matching. Given that the genetic matching algorithm optimally selects the weight to construct a distance measure among the weighted Mahalanobis distances based on matching performance, it usually outperforms Mahalanobis distance, which is a special case of weighted Mahalanobis distances. Compared to propensity score matching (PSM), genetic matching does not require an accurate or precisely estimated parametric model for propensity scores. While the performance of PSM is dependent on the performance of the propensity model, it is difficult to construct an accurate and precise propensity score model on 41 types of work activity variables due to the high-dimensional characteristics. For this reason, our genetic matching technique is expected to outperform the other alternative matching techniques, resulting in the fewest number of "large" standardized mean differences (SMD) among the variables used for matching.

Figure 1 provides the plots of the SMD of each work activity variable before and after our matching procedure. As a rule of thumb, an SMD value above 0.25 is considered large, which means that there is a serious imbalance (Stuart 2010). Before matching, the SMD is above 0.25 for many work activity variables, implying that there are serious imbalances in the size of the work activities between the treatment and control groups. After matching, no variable has an SMD larger than 0.25. Therefore, we conclude that our matching improves the balance between the observations in the IT-intensive and non-IT-intensive groups.

Figure 1. Standardized Mean Difference (SMD) Pre- and Post- Matching



The results of analyzing the matched data (shown in Table 8) are broadly consistent with our main findings, which suggests that endogeneity may not be a serious concern in our analysis. The main effect of IT on specialization in Model (2) is significantly positive ($\beta = 0.019$, $p < 0.01$). In addition, the moderating effect of urban agglomeration is significantly positive ($\beta = 0.064$, $p < 0.01$). These results support the robustness of our main analysis. However, the moderating effect of cognitive skill is not significant in this analysis ($\beta = -0.008$, $p > 0.10$), which implies that the moderating effect of cognitive skills may be weak.

Table 8. Estimation Results After Matching

Dependent variable	Specialization		
Model	(1)	(2)	(3)
IT-Intensive Group		0.019 *** (0.003)	-0.010 (0.022)
Cognitive Skill	0.021 *** (0.005)	0.008 * (0.005)	0.012 (0.004)
Urban Agglomeration	0.038 *** (0.008)	0.021 *** (0.007)	- 0.009 (0.009)
Professional Group	0.025 *** (0.004)	0.028 *** (0.003)	0.027 *** (0.003)
Office Clerk Group	0.049 *** (0.004)	0.045 *** (0.004)	0.046 *** (0.004)
Operator Group	0.037 *** (0.006)	0.020 *** (0.006)	0.022 *** (0.006)
Manual Worker Group	0.019 *** (0.004)	0.009 ** (0.004)	0.010 ** (0.005)
IT-Intensive Group × Cognitive Skill			-0.008 (0.005)
IT-Intensive Group × Urban Agglomeration			0.064 *** (0.015)
Constant	0.023 (0.004)	0.071 *** (0.017)	0.083 *** (0.018)

R-squared	0.32	0.38	0.39
F – Statistics	32.71	35.01	31.54
Observations/ Groups	1974/16	1974/16	1974/16
Notes: *p<0.10, **p<0.05, *** p<0.01; all two-tailed tests. Unstandardized coefficients are reported. Standard errors are in parentheses.			

8. Discussion and Conclusion

8.1.Discussion of Key Findings

Our goal in this research was to examine the association between IT and specialization, while also considering whether the strength of the impact varies depending on two occupational characteristics, cognitive skill level and the degree of urban agglomeration. I found that IT is significantly associated with an increase in an individual worker's specialization. On average, a one-unit increase in IT is associated with a 0.006-unit increase in the degree of specialization. In addition, examining the differential effects of IT by occupation characteristics, I found that the cognitive skill level and urban agglomeration level positively moderate the impact of IT on specialization.

Our findings reveal several interesting patterns. First, the average positive impact of IT on worker specialization that I found suggests that the positive impact of IT on specialization outweighs the negative impact. As I explicated earlier, while IT can decrease the average degree of specialization by substituting for simple tasks through automation and offshoring, and by creating new complex tasks that are difficult to coordinate (Acemoglu and Autor 2011; Drucker 1999; Lindbeck and Snower 2000), IT can also improve the coordination of such complex tasks by facilitating the division of labor, as IT can reduce information asymmetry and uncertainty among workers associated with coordinating complex tasks (Gurbaxani and Whang 1991; Malone 2011). Our empirical evidence suggests that the specialization-enhancing mechanism of

IT is more salient than IT's specialization-diminishing mechanism, rendering a positive net effect of IT on specialization.

Second, the differential impacts of IT on specialization by two occupational characteristics, namely, cognitive skills and urban agglomeration, show how IT affects specialization, which depends on the occupational characteristics that reduce external coordination costs for complex tasks. While the degree of specialization is limited by external coordination costs among workers (Becker and Murphy 1992), information asymmetry and uncertainty from coordinating complex tasks can increase such external coordination costs (Williamson 1973). Because cognitive skills help workers process information more proficiently (which facilitates cross-worker coordination involved in performing complex tasks), workers with higher cognitive skills can be more specialized when they use IT, as they can decrease information asymmetry and uncertainty to a greater extent. Similarly, workers in urban areas can have more frequent interactions (especially face-to-face) to share and exchange information, which can reduce external coordination costs (Becker and Murphy 1992; Duranton and Puga 2004). Therefore, occupations with higher degrees of urban agglomeration can coordinate complex tasks created by IT more efficiently. As a result, the degree of urban agglomeration can amplify the positive effect of IT on specialization.

Third, our findings imply that specialization is an important pathway through which IT contributes to wage growth. While several prior studies suggest that IT contributes to wage growth (Acemoglu and Autor 2011; Autor et al. 2003; Mithas and Whitaker 2007), our results suggest that a significant portion (12.5%) of IT's effect on wages is mediated by specialization. Albeit preliminary, the results indicate that specialization is an important mechanism through which IT affects workers' wages, which represent their productivity.

8.2.Contributions and Implications

This study makes several contributions. First, our study provides a new theoretical and empirical approach to investigate the relationship between IT and worker specialization based on the TCE perspective. To date, research on the relationship between IT and specialization has been scarce and equivocal. While a few studies (Drucker 1999; Lindbeck and Snower 2000) have argued that IT adoption might decrease the degree of worker specialization by substituting for routine tasks, there are several studies that suggest, both theoretically and empirically, that IT might increase the degree of specialization for some occupations (Malone 2011; Mintzberg 1979; Mintzberg 1981; Pinsonneault and Rivard 1998). Our study makes a meaningful contribution to this research stream by developing a conceptual framework based on previous work on coordination costs (Mintzberg 1979, Becker and Murphy 1992, Gurbaxani and Whang 1992) and by providing empirical evidence on how IT affects the degree of specialization in various occupations.

Second, our findings shed new light on how IT has changed the nature of work. Specifically, our study provides novel insights to the RBTC literature (Acemoglu and Autor 2011; Acemoglu and Restrepo 2018; Autor et al. 2003; Spitz-Oener 2006; Tambe and Hitt 2012) by drawing on prior research regarding the impact of IT on coordination structures (Gurbaxani and Whang 1991; Malone and Crowston 1994; Malone 2011). While the RBTC literature has mainly focused on how the labor-substituting properties of automation and offshoring would change the demand for labor, our study delved into how IT capabilities would affect the degree of specialization, thereby expanding the scope of enquiry. In addition, while previous studies from the TCE perspective have examined how IT might change the size and scope of firms by affecting coordination costs (Brynjolfsson et al. 1994a; Gurbaxani and Whang 1991; Hitt 1999;

Im et al. 2013; Ray et al. 2013), I adapt the concept of coordination costs to individual workers to investigate how IT-driven coordination across individual workers would affect the extent to which they are specialized. Moreover, I provide theoretical explanations on how cognitive skills and urban proximity can enhance the positive effect of IT on specialization and provide supporting evidence. Hence, this research complements the RBTC literature by providing an understanding of how technological changes have increased the value of cognitive skills (Autor et al. 2003; Bresnahan et al. 2002; Spitz-Oener 2006) and urban agglomeration (Autor 2019; Frank et al. 2018; Gaspar and Glaeser 1998; Leamer and Storper 2001).

Third, the findings enhance our understanding of how IT contributes to productivity (Acemoglu et al. 2014; Brynjolfsson and Hitt 1996; Han et al. 2011; Mittal and Nault 2009). Because specialization allows a production system to access diverse specialized knowledge, it has been regarded as an important mechanism in explaining how reduced coordination costs lead to economic development (Becker and Murphy 1992; Romer 1987; Smith 2010; Yang and Borland 1991; Young 1928). In this research, I suggest that specialization is a micro-foundation linking IT to productivity and present empirical evidence confirming that specialization is an important pathway through which IT increases wages. Therefore, our study makes a meaningful contribution to the IT productivity literature by suggesting an intermediate mechanism (i.e., specialization) for how IT increases productivity from the perspective of coordination costs (Aral et al. 2012; Brynjolfsson et al. 1994a; Goes et al. 2018; Gurbaxani and Whang 1991; Hitt 1999; Im et al. 2013; Malone and Crowston 1994; Ray et al. 2013).

Lastly, this study provides important insights to practitioners with respect to the design of workers' task bundles in their organizations. As firms adopt more IT, they must often change various aspects of their organizational structure to capture greater value from IT (Aral et al.

2010; Bresnahan et al. 2002). Our study provides guidance regarding specialization, which is an important parameter in designing organizational structures (Mintzberg 1979). Specifically, our findings suggest that increasing IT adoption and usage can lead to increased specialization, which result in higher productivity, especially for workers with high levels of cognitive skills and those located in urban areas. Therefore, firms seeking to increase the specialization of their workers need to invest more in IT and incentivize their workers to use IT more intensively. In addition, our findings also suggest that firms need to increase the cognitive skill level and the degree of urban agglomeration of their workforce to benefit more from the specialization-enhancing effects of IT. IT-driven specialization can lead a to a 'win-win' situation where firms can achieve productivity gains, while individual workers can attain higher wages.

8.3.Limitations and Future Research

Our study is not without limitations. First, our data contain missing data due to the nature of the data collection procedure of O*NET. Although it is not substantial, given that the missing mechanism is not directly related to our main IT variable, bias may exist in estimating the effect size of IT on specialization. As O*NET is one of a few reliable databases containing the task contents of US workers for a sufficiently long period, I believe that this research has made important contributions. However, there should be further analysis by using other databases to increase the credibility of this research. Second, our study is based on occupational-level analyses. Because specialization concerns general phenomena, diverse levels of production systems are involved such as firm, industrial, national, and international levels. In addition, specialization provides an approach to explain how improved coordination within and between such diverse economic systems by IT can contribute to productivity growth by facilitating the division of labor. Therefore, future studies should complement our findings by conducting analyses at different levels (e.g., industry level). Such analyses will be able to provide additional insights regarding how IT impacts various levels of economic systems through specialization.

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Appendices

Appendix 1. Occupational Group Category

The occupational group is operationalized based on SOC major groups. The occupations in the SOC system are classified at four levels of aggregation: major group, minor group, broad occupation, and detailed occupation. There are 23 major groups in the SOC system. We aggregated those 23 major groups into our five types of occupation groups. The detailed classification is provided in Table 9.

Table 9. Occupational Group and SOC

Occupational Type	SOC Major Groups (2-digit Major Group)	Example (SOC Detailed Occupation Code)	Definition	Remark
Manager	Management (11)	Chief Executives (11-1011), General and Operations Managers (11-1021), First-line Supervisors of Housekeeping and Janitorial Workers (37-1011)	Workers who perform managerial tasks such as coordinating, information processing, and decision-making for the organized activities of other workers	Even though an occupation is not in the management major groups, some occupations with “supervisors” in the name are regarded as managers.
Professional	Business (13), Science (15,17,19), Social (21), Legal (23), Education (25), Art (27), Healthcare (29)	Accountants and Auditors (13-2011), Computer Programmers (15-1251), Community Health Workers (21-1094), Anesthesiologists (29-1211)	Workers who perform complex cognitive tasks for administrative functions such as designing organizational structures, performing legal tasks, and developing technical systems	
Operator	Production Occupations (51)	Team Assemblers (51-2092)	Workers who perform basic work related directly to product production	
Office Clerk	Sales (41), Office and Administrative Support (43)	Cashiers (41-2010), Production, Planning, and Expediting Clerks (43-5061),	Workers who perform simple cognitive tasks for managers and professionals	

		Billing and Posting Clerks (43-3020)		
Manual Service Worker	Healthcare Support (31), Protective Service (33), Food Preparation and Serving (35), Cleaning (37), Personal Care (39), Farming, Fishing, Forestry (45), Construction (47), Mechanics (49), Transportation (53)	Medical Equipment Preparers (31-9093), Police and Sheriff’s Patrol Officers (33-3051), Bus Drivers, School (53-3051)	Workers who work in an uncontrolled environment outside a large organization.	

Appendix 2 – Mintzberg's Framework of Occupational Specialization (1979)

Mintzberg (1979) provides a framework on how the different complexities of occupational tasks are associated with their degrees of specialization. This section reinterprets his framework based on our specialization research. His framework contains four types of occupation: unskilled jobs, professionals, first-line managers, and managers. Unskilled jobs such as factory assemblers and office clerks are mainly coordinated by process standardization. Because such jobs follow a specified process, their work outputs are standardized, and the external coordination costs to manage the interdependencies among their tasks with other workers are small. Therefore, their tasks can be divided into a small scope of subtasks and separately assigned to a massive number of workers. As a result, they are highly specialized to attain the benefits of specialization.

Professionals refer to workers who require professional knowledge for their occupational tasks such as strategy development or legal services. Even though they produce only a narrow scope of tasks for external partners, such professional services require significant amounts of intermediate tasks due to their complexity. For example, medical surgeons performing heart surgery engage in direct tasks such as cutting and sewing. However, such simple actions require significant amounts of underlying tasks such as collecting information, synthesizing such information, making decisions, and implementing such decisions. These interdependent processes require intensive professional knowledge acquired from training and experience. Due to the complexity of these processes, the external coordination costs to outsource such intermediate tasks are too high. Therefore, professionals must perform those intermediate tasks by themselves. As a result, even though professionals provide a narrow scope of services for other co-workers or customers, their professional services require diverse kinds of interdependent tasks that must be done by themselves Due to the vertically integrated nature of professional tasks, the degrees of specialization in professional occupations are lower than those in low-skilled occupations.

Unlike professionals and low-skilled jobs providing specialized labor, managerial occupations perform diverse tasks for external partners. Superficially, managers specialize in communication activities such as meetings and e-mail. However, such interpersonal tasks are channels of managerial occupations to engage in diverse issues involving other workers' tasks because they are responsible for integrating the divided tasks of other workers. Therefore, they are involved in diverse issues from different parts of the division-of-labor system, and they mutually adjust such issues with external partners to coordinate their different perspective and positions. Because those diverse tasks in managerial occupations are highly complex and require coordination, the external coordination costs are high. Hence, people in managerial occupations must perform these diverse tasks by themselves.

In addition, most managerial occupations are also vertically integrated; thus, most of the tasks are used as intermediate tasks for themselves. For example, they must collect information for analysis and synthesis. They must also make rules and standards to integrate other workers' tasks using the synthesized information. Such flows of managerial tasks are difficult to be divide due to their complexity. However, this degree of vertical integration in managerial tasks varies by the organizational hierarchy. The tasks of the lowest-level managers, who directly manage the low-skilled workers, are less vertically integrated; thus, the low-skilled workers get directives and information from their supervising managers. On the other hand, top-level managers' tasks are more vertically integrated; thus, they must manage these tasks by themselves. Due to the high internal and external interdependencies of managerial tasks, managerial occupations perform a wide variety of tasks. These managerial tasks are characterized by their brevity, variety and fragmentation; moreover, managerial occupations are the least specialized occupations (Kurke and Aldrich 1983; Mintzberg 1973; Mintzberg 1979; Mintzberg 2009; Tengblad 2006).

Given that the specialization of professionals and managerial occupations is low, the internal coordination and learning costs of those occupations are high compared to those of low-skilled jobs because they must perform more diverse tasks. For the reason, high-skilled workers, in terms of work experience or education (Acemoglu and Autor 2011), are assigned to such professional and managerial positions. Due to their high skill levels, high- skilled workers have more skills compared to low-skilled workers. Hence, they can perform roles that require high learning and internal coordination costs. Through such organizational practices, potential problems resulting from low degrees of specialization in managerial and professional occupations can be addressed. Mintzberg's (1979) framework of the specialization by occupational group is summarized in Table 10.

Table 10. Specialization by Occupational Group

Occupational Type	Description	Specialization	Skill Level	Example
Manager	People charged with overall responsibility for the organization	Low	High	President
Lowest-level Manager	People directly supervise and manage operators	Moderate	Middle	Foreman
Professional	People use complex skills to do their tasks	Moderate	High	Strategic Planner
Unskilled Jobs	People who directly engage in simple production and administrative tasks	High	Low	Machine Operator

The positive effect of IT usage on the degree of specialization in the first essay suggests that IT usage reduces the coordination costs for division of labor (across workers). This implies that the positive mechanism of IT on the coordination is stronger than the negative mechanism. However, while the negative mechanism between IT and the degree of specialization is because IT usage increases the complex tasks that are hard to be coordinated, many previous studies suggest that IT usage does not improve the coordination of the complex tasks because IT network is typically not effective in transferring tacit knowledge (Acemoglu and Autor 2011; Kanawattanachai and Yoo 2007; Mani et al. 2014; Mithas and Whitaker 2007). Therefore, it requires an explanation how IT usage reduces the coordination costs of the complex tasks to explain why the negative mechanism is weaker than the positive mechanism in our research context.

One potential explanation how IT improves the coordination of the complex tasks is that IT might facilitate urban agglomeration, which improves the coordination of complex tasks (Leamer and Storper 2001). As tacit knowledge, or complex information, can be effectively transferred when workers are physical close by allowing face-to-face communication (Nonaka and Konno 1998; Storper and Venables 2004), urban agglomeration enables workers to exchange complex information which is required for coordinating complex tasks. Similarly, the positive moderating effect of urban agglomeration found in the first essay implies that urban agglomeration weakens the negative mechanism between IT usage and specialization. Therefore, if IT facilitates urban agglomeration, such agglomeration will weaken the negative effect of IT on the specialization, entailing to the positive effect of IT on the degree of specialization observed in the first essay.

In the second essay, I examine the relationship between IT usage and urban agglomeration. By doing so, we can build a hypothetical mechanism how IT can improve the coordination of the complex tasks that is not effectively coordinated by IT network, and explain the positive effect of IT usage on the degree of specialization in the first essay.

CHAPTER TWO – Does IT Facilitate Urban Agglomeration? An Empirical Analysis

1. Introduction

Since the beginning of information technology (IT) revolution, many scholars and practitioners have predicted that IT (especially the internet) would largely eliminate the need for physical proximity and fundamentally replace the role of cities in organizing economic activities. Since IT enables people to communicate with one another and exchange complex messages without having to be in close distance, Toffler (1970) predicted that cities, which provide physical proximity, would lose their advantages due to "the shift of work from both office and factory back into the home." Indeed, IT has afforded people the capabilities to work remotely such that they can collaborate across geographical boundaries. Over the past two decades, offshoring and international trades driven by IT have been important trends (Mani et al. 2014; Mithas and Whitaker 2007). In this sense, IT might have reduced the significance of urban areas that provide physical proximity for workers.

However, many researchers have also suggested that IT also has made the world more “spiky” such that they require more physical proximity for their work (Florida 2017; Mithas and Whitaker 2007). Even though IT has been actively deployed for the last few decades, the population living in urban areas has also grown (Autor 2019). Workers have clustered to big cities, so-called “superstar cities”, where a variety of technological innovations have been created. Given that the benefits of urban agglomeration stem from physical proximity among workers (Becker and Murphy 1992), it is possible that IT may have enhanced the value of physical proximity. For example, Tambe and Hitt (2014) found that physical proximity is an important factor that drives productivity spillover from IT investment. Given these conflicting views, it is unclear whether the use of IT facilitates urban agglomeration of work activities or not, making it essentially an empirical question.

The relationship between IT and urban agglomeration of jobs is important for growth strategy and/or urban planning. As urban agglomeration is an important source of productivity improvement, investigating how IT is related to urban agglomeration can help us design a strategy to use IT to increase productivity. In addition, given that urban agglomeration can cause social issues such as gentrification, high living costs, and infrastructure burden, understanding the relationship can help us predict how technical change would affect future trends of urban agglomeration so that proper policies for addressing the social issues can be developed.

One theoretical perspective that has been used to explain the relationship between IT and urban agglomeration is that of coordination. Studies in urban economics literature (Gaspar and Glaeser 1998; Ioannides et al. 2008; Leamer and Storper 2001) suggest complementarity between IT and the demand for urban areas. While IT facilitates the economic exchange across distant places by improving the capability to exchange information, IT cannot perfectly substitute for the face-to-face communication. Therefore, they predicted that the demand for the face-to-face communication would increase as the long distant economic exchange enabled by IT becomes more prevalent. However, previous studies do not provide empirical evidence regarding how the urban agglomeration of the workers is related to coordination costs. Specifically, although the previous theoretical mechanism is based on coordination costs, there has been a paucity of empirical evidence on whether the effects of IT on urban agglomeration depend on the coordination-related factors.

In this research, I develop theoretical arguments regarding how IT facilitates the urban agglomeration of workers, defined as the proportion of the occupation employed in metropolitan areas, by affecting their coordination costs (Acemoglu and Restrepo 2018; Autor et al. 2003; Gurbaxani and Whang 1991; Malone and Crowston 1994) and how these effects vary depending on two coordination-related occupational characteristics, complex communication task intensity, which refers to the task for complex information exchange, and complex manual task intensity, which requires complex physical activities. By doing so, I suggest that the impact of IT on urban agglomeration is related to the impact of IT on coordination costs. Specifically, I address the following questions: *(1) Is IT associated with an increase in the urban agglomeration of occupations; and (2) does the strength of the relationship vary depending on the occupational characteristics related to coordination costs?*

To address the questions, I employ an occupation-year panel analysis based on data from the US Occupational Network (O*NET) and Occupational Economics Statistic (OES) containing 656 occupations during the period 2003-2019; the data contains information about the employment for each occupation by region and various occupational attributes including the intensity of IT usage. I conduct a panel regression analysis weighted by the number of employment of occupation-year observations. I find that on average the use of IT is significantly associated with the degree of urban agglomeration of an occupation. Moreover, I find evidence such impact of IT on urban agglomeration is stronger for the occupations conducting more complex communication tasks and complex manual tasks.

This study makes several contributions. First, this study provides what I believe to be the first occupational-level empirical evidence of the complementarity between IT and urban agglomeration and the moderating effects of coordination-related occupational characteristics. Although there have been several studies examining the relationship between IT and urban agglomeration (Autor 2019; Gaspar and Glaeser 1998; Leamer and Storper 2001; Storper and

Venables 2004), they do not provide direct evidence linking IT usage and urban agglomeration at occupational level. Our study contributes to these studies by empirically showing that occupations using more IT are more likely to be in urban areas, and such tendency differs according to the occupational characteristics related with coordination. Second, I contribute to the literature on the future of work. This study extends previous studies in IS and economics on how IT changes the nature of work (Acemoglu and Restrepo 2018; Autor 2019; Autor et al. 2003; Lin 2011). I theorize how such changes facilitate the urban agglomeration phenomenon by increasing the complexity of work, which requires physical proximity for effective coordination. Therefore, our study contributes to the literature on the future of work, specifically, regarding how locations of work are influenced by IT usage.

2. Related Literature

This study draws on the prior literature that broadly investigates the mechanisms regarding how IT changes urban agglomeration structure (Fabian et al. 2020; Gaspar and Glaeser 1998; Leamer and Storper 2001) by changing the nature of work (Acemoglu and Autor 2011; Autor et al. 2003; Bresnahan et al. 2002; Gurbaxani and Whang 1991; Mithas and Whitaker 2007). Specifically, I use the concept of coordination costs, defined as costs for managing the interdependency among tasks in a production system (Malone and Crowston 1994), as a basis of our theoretical framework. In this study, coordination costs include various types of information costs, such as monitoring cost, agency cost, contract cost, and communication cost, which originate from information asymmetry among production agents, as well as transportation costs for transferring physical objects among production agents (Becker and Murphy 1992; Gurbaxani and Whang 1991).

One approach to explaining the relationship between IT and urban agglomeration focuses on the substitutive and complementary role of IT for urban areas from the perspective of coordination (Duranton and Puga 2005; Duranton and Puga 2015; Gaspar and Glaeser 1998; Ioannides et al. 2008; Leamer and Storper 2001; Mithas and Whitaker 2007). This approach has been used to explain the relationship between IT and urban agglomeration based on how IT changes the nature of work. Specifically, while IT can deagglomerate simple tasks from urban areas by allowing them to be coordinated across geographical boundaries, or to be automated, IT can also increase complex and time-critical tasks that require face-to-face communication (Acemoglu and Autor 2011; Autor et al. 2003; Mithas and Whitaker 2007). For example, IT can automate, and offshore simple routine tasks such as assembly tasks or simple calculation, while at the same time creating new complex tasks, of which process is not clear and explicit (Autor et al. 2003), such as programming, or developing digital business models. As a result, this stream of research predicted that IT would further facilitate clustering of complex economic activities in urban areas.

However, the previous research has been mainly theoretical, and there is a lack of empirical evidence on the relationship between IT and urban agglomeration in the literature (Duranton and Puga 2015). An exception is Gaspar and Glaeser (1998) who provided some empirical evidence that IT facilitates the urban agglomeration. However, their evidence is indirect because they examine the relationship between telephone use and urban agglomeration. As IT affords more advanced capabilities for exchanging information and knowledge compared to telephone, their finding cannot be extrapolated to understanding the relationship between IT and urban agglomeration. In addition, although they argue that the relationship between IT and urban agglomeration is dependent on how IT affects coordination costs, they have not provided any empirical evidence regarding the role of coordination-related occupational characteristics in the relationship between IT and urban agglomeration. A summary of the previous key empirical research is provided in Table 11.

Table 11. Related Empirical Research

Paper	Analysis Unit	Key Argument	Key Finding
Gaspar and Glaeser (1998)	Region	IT would facilitate urban agglomeration.	Telephone usage is positively associated with urbanization of Japanese prefecture.
Ioannides et al. (2008)	Country	ICT would facilitate urban de-agglomeration	Internet user per capita reduces the variation in city sizes.
Mithas and Whitaker (2007)	Occupation	What kinds of occupational characteristics facilitates service offshoring	There is a positive association between skill level and information intensity on service offshoring.
Forman et al. (2005)	Establishment	Population density does not affect the adoption of simple ICT but increases the adoption of complex ICT for enhancement.	There is a positive association between population density and adoption rate of complex ICT, but the relationship is not significant for simple ICT.
Tranos and Ioannides (2021)	Country	IT would facilitate urban agglomeration.	ICT adoption reduces the variation in city sizes.

In this research, I develop an integrative framework for explaining how IT affects urban agglomeration from the coordination perspective and provide empirical evidence regarding the association between IT usage and the degree of urban agglomeration and the moderating effects of occupational characteristics related to coordination. By doing so I highlight that the relationship between IT and urban agglomeration is dependent on the role of IT in substituting for the proximity provided by urban areas in coordinating across workers.

3. Theoretical Framework

3.1. Coordination Costs and Urban Agglomeration

I begin by explaining the mechanisms underlying urban agglomeration. According to Becker and Murphy (1992), the physical proximity among residents is the main reason for urban agglomeration. As workers are located closer together, they can reduce the coordination costs for interacting with one another. They can meet more frequently to exchange information, which can reduce the information asymmetry among them. In addition, they can also save the costs for moving physical objects when they are closely located. Therefore, locating production agents closely facilitates coordination among them, and the reduced coordination costs can lower overall transaction costs. Such low transaction costs lead to the emergence of large markets for various products and services based on a large and complex division-of-labor system where they can be more specialized (Becker and Murphy 1992; Duranton and Puga 2004). In sum, collocation increases productivity of the residents by helping them to reduce coordination costs and facilitates their specialization.

Especially, complex tasks involving a large amount of tacit knowledge are more effectively coordinated by face-to-face communication (Storper and Venables 2004). Tacit knowledge, referring to a part of knowledge that is hard to be expressed by a symbolic system such as language, formula, and figures (Nonaka 1994), cannot be easily transferred without proximate interactions. For example, theoretical perspectives, common sense, or mental models are examples of tacit knowledge that cannot be wholly expressed in an explicit manner. Therefore, it is difficult to exchange tacit knowledge through such communication methods as letters, and e-mails; physical proximity is required to share tacit knowledge (Nonaka and Konno 1998). Therefore, physical proximity plays an important role for coordinating tacit-knowledge intensive tasks.

Based on this coordination cost perspective, I suggest that the main benefits of urban agglomeration are low coordination costs of the urban areas due to the high population density and physical proximity, especially for carrying out complex tasks involving intensive tacit knowledge. Therefore, occupations incurring relatively low coordination costs can be located far from the urban areas to benefit from low land costs of rural areas. On the other hand, if a production process requires a great deal of coordination, it should be located in urban areas to reduce the coordination costs.

3.2. Trade-off between Urban Costs and Coordination Costs

Although urban agglomeration provides benefits in terms of low coordination costs based on physical proximity, not all workers can be located at the urban areas. There is a selection process for workers' locations according to the heterogenous characteristics of their production systems. In the urban study literature (Duranton and Puga 2015), a monocentric urban model is used to analyze the location choice of the agents. The model assumes that the coordination costs in a core agglomerated urban area, where the economic agents are agglomerated, are low due to physical proximity among the agents. However, the prices for workers to pay to be located in such a core are also high. Due to the high demand for the physical proximity in the core areas, the land prices of the core areas are high (Duranton and Puga 2015). In addition, there are congestion costs (e.g., traffic costs) due to the dense population of the urban areas (Henderson 1974).

Under this setting, the optimal locations are determined according to the features of their production system. Since different occupations employ different types of production systems, they optimize their locations according to the relative benefits (low coordination costs) and costs (high "urban costs") of urban areas vis-à-vis rural areas. By moving away from the core, the economic agents can save on land prices; however, they cannot benefit from the low coordination costs to access a variety of specialized goods and services in the agglomerated core area. Therefore, the optimal location of a production agent is determined by the cost structure of its production system in terms of the coordination costs and the urban costs. If a production system requires large physical space (e.g., workers in the manufacturing industry), they are likely located far from the core area to save the urban cost. On the other hand, if a production system requires complex interactions among workers (e.g., personal trainers), they have to be located in the urban areas to have more benefits in terms of the low coordination costs. Against this backdrop, I next develop hypotheses.

4. Hypotheses Development

4.1. IT and Urban Agglomeration

Theoretically, it is not clear whether IT would accelerate or decelerate urban agglomeration of jobs. Because the degree of urban agglomeration of an occupation is determined by the level of coordination required by the occupation as discussed above, the impact of IT on urban agglomeration depends on whether IT increases or decreases coordination costs. If IT increases coordination costs, IT will increase the demand for urban proximity among workers and thus accelerate urban agglomeration; otherwise, IT will substitute for the physical proximity, and hence decelerate urban agglomeration. The overall impact of IT on coordination costs, however, is not clear due to the coexistence of two alternative views. On one hand, IT can decrease coordination costs by reducing information costs (Gurbaraxi and Whang 1992): by improving information processing capability, IT reduces information costs arising from information asymmetry among workers. As a result, workers are able to coordinate remotely across geographical boundaries (e.g., offshoring) (Acemoglu and Autor 2011; Mithas and Whitaker 2007). In this case, IT can substitute for the physical proximity provided by urban areas by reducing coordination costs.

For example, workers can communicate more efficiently with the other co-workers by using many different types of communication tools such as e-mail, and mobile messenger. Such efficient communication tools allow workers to exchange information to meet an agreement and to share the same understanding across the geographical and organizational boundaries. Thanks to such improved coordination process, workers can outsource their marginal tasks to the specialists who are most suitable to perform the tasks regardless of the workers' location. As a result of IT usage as a communication tool, the workers do not need to meet in person, and can move away from the urban center to avoid the high living costs.

On the other hand, IT can also increase coordination costs by increasing complex tasks that require intensive tacit knowledge. According to the SBTC literature, while IT can substitute for relatively simple and standardized tasks through offshoring and automation, IT can also create complex tasks requiring tacit knowledge (Acemoglu and Autor 2011; Acemoglu and Restrepo 2018; Autor et al. 2003). For example, IT increases the amount of complex analytical tasks such as programming or complex managerial tasks such as organizing co-workers across the geographical boundary. Since such tacit knowledge cannot be expressed in systematic symbols, it is hard to be communicated by IT network. Therefore, IT network is not effective for exchanging information to coordinate tacit knowledge-intensive complex tasks

(Kanawattanachai and Yoo 2007; Mani et al. 2014; Mithas and Whitaker 2007). Tacit knowledge can be shared more effectively when the workers are closer together (Nonaka and Konno 1998), workers would cluster in urban areas to coordinate such tacit knowledge-intensive tasks created by IT. Therefore, IT can facilitate the urban agglomeration by creating complex tasks that are hard to be coordinated by IT network across the geographical boundary.

One example of such change is office automation. As many office automation tools such as Microsoft Excel, Words, and PowerPoints are adopted in the office, they automate many time-consuming repetitive tasks, such as text editing or calculation. While these software tools replace highly specialized typists and human computers, they also increase the amounts of non-replaceable tasks such as writing, data analysis, and presentation as they can easily conduct such tasks using labor saving features of office automation tools (Acemoglu and Autor 2011; Autor et al. 2003). As these tasks are more complex compared to typing or simple calculation, these new tasks consist of highly dependent subtasks that are not divisible such as modelling, designing presentation slides, and formulating hypothesis. Given that these complex ideas are better exchanged through in-person meetings, IT usage and associated increased complex tasks facilitate the urban agglomeration.

Taken together, whether IT increases or decreases coordination costs depends on the relative magnitude of these two countervailing effects. Although the impact of IT on coordination costs is unclear, I argue that the net effect of IT would be to increase the demand for physical proximity, thereby facilitating urban agglomeration, because IT has been found to increase the amount of complex tasks in the US economy (Acemoglu and Autor 2011; Mithas and Whitaker 2007). Therefore, I posit:

H1: IT usage is positively associated with the degree of urban agglomeration.

4.2. Moderating Role of Complex Communication Task Intensity

Although IT has two countervailing effects on urban agglomeration, the strength of the effect can vary according to the nature of tasks. As our theoretical mechanism is based on the capability of IT to substitute for the benefits of the urban area in reducing coordination costs, the impact of IT on urban deagglomeration is expected to be weakened when an occupation involves tasks requiring more complex coordination that IT cannot reduce the coordination costs. In this section, I argue that the impact of IT on urban deagglomeration is weakened for the occupations wherein workers need to exchange complex information for others to a greater extent. Examples of such "complex communication tasks" is communicating organizational policies, interpreting medical test results to patients or family members, and teaching a school subject for students.

While IT can deagglomerate workers from the urban area by reducing the coordination costs to exchange information, such effects are dependent on the substitutability of IT for the role of urban area in coordination. If IT cannot substitute the role of urban area much, the effect of urban deagglomeration is expected to be weaker. Given that the complex communication task requires to exchange large amount information (e.g., explaining medical test results to non-experts), IT can only partially substitute for the role of urban areas in exchanging such information. While explicit information (e.g., presenting medical test results) can be transferred by electronic networks, it is difficult to convey tacit part of complex communication (e.g., identifying the part that the audience may misunderstand) as electronic networks can transfer only explicit knowledge (Acemoglu and Restrepo 2018; Autor et al. 2003; Mithas and Whitaker 2007). Therefore, IT cannot fully substitute for the role of urban areas in exchanging complex information because the complex communication involved requires intensive tacit knowledge which cannot be easily transferred through IT networks.

For example, IT network allows to send medical test results to farther place, therefore, workers conducting medical tests can be located away from the urban area. However, the medical doctors explaining the test results for their patients should located in the urban area to communicate with their patients. As their patients are non-experts who does not have much medical knowledge, there is large information asymmetry and uncertainty between the patients and the medical doctors. Therefore, it is important for the medical doctors to build a trust or rapport that their patients believe that their doctors are trustworthy. Since this process requires to exchange non-codifiable information, the face-to-face communication is the most effective, hence, hard to be substituted by IT network. As a result, the urban deagglomeration caused by IT usage is weaker for the medical doctors who requires complex communication with the patients. Therefore, I posit:

H2: The association between IT and urban agglomeration (deagglomeration) is stronger (weaker) for the occupations conducting with higher complex communication task intensity.

4.3. Moderating Role of Complex Manual Task Intensity

I argue that the impact of IT on urban agglomeration is dependent on another occupational characteristic related to coordination costs. Specifically, I argue that the magnitude of the impact of IT on urban deagglomeration is weaker for workers conducting more complex physical tasks, such as driving, cleaning, servings, and constructing (Acemoglu and Autor 2011; Mithas and Whitaker 2007).

Although, IT can improve the coordination for the complex manual task by reducing the coordination costs related with the information exchange, IT cannot fully substitute for the physical proximity of urban areas, specifically for reducing the transportation costs. IT can partially facilitate coordination of complex manual tasks by improving the exchange of explicit information required to coordinate such tasks. However, IT cannot effectively reduce the transportation costs the workers incur to be physically present to conduct complex manual tasks as IT network cannot transport the physical objects (Acemoglu and Autor 2011; Mithas and Whitaker 2007).

For example, Uber drivers can easily find their customers by using Uber app as it helps efficiently transfer the locational information between customers and drivers. However, the uber drivers have to physically present at specific location as per the demand of the clients. Therefore, such complex manual tasks incur significant transportation costs. These transportation costs cannot be effectively reduced by Uber application while the physical proximity in the urban area can effectively reduce them. Therefore, IT network cannot fully substitute the role of the physical proximity in coordinating complex manual tasks, which results in weakening the impact of IT on urban deagglomeration. According to the above argument, I posit:

H3: The association between IT and urban agglomeration (deagglomeration) is stronger (weaker) for the occupations conducting more complex manual tasks.

5. Research Method

5.1. Data

I test our hypotheses using data from Occupational Network (O*NET) and Occupational Economic Survey (OES) for the period 2003-2019. 782 occupations were identified from O*NET database using 2010 standard occupational classification (SOC). O*NET is a database providing rich information about occupations for a sufficiently long time-period, and it has been widely used in prior research in both economics and IS (Autor and Acemoglu 2011, Tambe and Hitt 2012). O*NET database collects their occupational data based on the surveys of incumbent workers and opinions from occupational experts in O*NET.

Although our theoretical argument is at individual level, I use the occupational data in this research. Since there is a practical challenge to collect a reliable individual level data for long-time periods, I use the occupational level data from O*NET database Since the occupational data are the aggregated individual level data by occupation, the analysis of the occupational level data contains the information about individual level workers. Therefore, it leads to accurate results if there are no significant occupational variation of work characteristics within same occupation. Since occupational codes are assigned to the workers with similar work characteristics, using occupational level data has been used in many previous research (Acemoglu and Autor 2011; Autor et al. 2003; Tambe and Hitt 2012). To match the gap between the occupational level data and individual level theory, I use employment number of each occupation-year specific observation as a weight for each observation to analyze how IT is associated with the urban agglomeration for the average individual worker. For the reasons, I use occupational data in this research, although our theoretical arguments are at individual level.

Since O*NET database updates approximately 100 occupations annually, not every occupation is updated each year. For example, Chief Executive Officer has been updated 3 times; 2007, 2013, and 2014. In the original database, the missing values are imputed by last observation carry forward (LOCF) (imputing missing data using the most recent observations). Although LOCF is widely used in many clinical trials, there has been a criticism that LOCF may result in biased estimates (Council 2010). Specifically, because LOCF ignores the potential changes that may have happened after the last observation, it might cause a serious bias if such changes are significant.

Therefore, I use another approach, namely, complete-case analysis in which missing cases are discarded. This complete-case analysis is valid when the missing variable is completely at random (MCAR), that is, when the selection of missing data is independent of the focal variables, IT variable in our case. Since the incomplete update scheme of O*NET is not directly related to the IT variables, it is plausible to assume that our data satisfies the MCAR condition; therefore, the estimated impact IT on urban agglomeration is not biased. Although the sample size becomes smaller because the missing cases are discarded, resulting in a decrease in the power of test, MCAR is more accurate compared to LOCF as long as the remaining data are sufficient to precisely estimate the effect size (e.g., p-value is low enough to be statistically significant).

Our final samples consist of 1,974 occupation-year observations from 656 occupations over 2003-2019. In addition, I use the employment numbers and wage data from OES, a data collection program run by the US Bureau of Labor Statistics. Following previous research (Autor et al. 2003; Spitz-Oener 2006), I use the annual national employment number for each occupation as the weight for each occupation in the analysis to control for the influence of the occupation size.

5.2. Variables

To measure our dependent variable, the degree of urban agglomeration, which captures the extent of urban agglomeration of an occupation, I divide the total employment in all Metropolitan Statistical Areas (MSAs) by the total national employment for each occupation. An MSA is defined by the U.S. Office of Management and Budget (OMB) as having at least one urbanized area with a minimum population of 50,000. Our measure, the proportion of the employment located in MSAs, captures the degree to which workers in each occupation is hired in MSAs, and can represent the extent to which an occupation is in urban areas vis-à-vis non-urban areas.

Our main independent variable, IT, is a level measure of "Interacting with Computer Work Activity" descriptor. It measures the required skill level for using computers and computerized systems (including hardware and software), programming, writing software, setting up functions, entering data, or processing information. Basically, the variable reflects to what extent an occupation uses IT tools, and I use it as a proxy for the degree of IT usage. In the previous literature investigating the impact of IT on organizational performance, the amount of IT investment or IT workforce are used to measure IT use in the production process at the organizational level. Similarly, our IT variable captures the intensity of IT use in the individual-level production process since the intensity of interaction with computers reflects the extent to which IT is used by workers in each occupation.[3]

To test hypothesis 2 to examine the moderating effect of complex communication task intensity, I use the importance score of "Interpreting the Meaning of Information for Others" work activity descriptor in O*NET database as a proxy for complex communication task intensity. The importance score measures how important it is to translate or explain what information means and how it can be used. This score is high for occupations that need to deliver complex information for the others, such as Postsecondary Psychology Teachers, Genetic Counselors, Hospitalists in O*NET database. Since our theoretical construct, complex communication intensity, is related to how much they perform exchanging the complex information with the others, the current measure can be used as a proxy for our construct.

[3] In addition, I also used the importance score of "Interacting with computer" work activity descriptor in O*NET database as an alternative measure of IT usage, and obtained qualitatively similar results.

To test hypothesis 3, I use the importance score of “Performing General Physical Activities” work activity descriptor in O*NET database as a proxy for complex manual task intensity. The importance score measures how it is important to perform physical activities that require considerable use of your arms and legs and moving your whole body, such as climbing, lifting, balancing, walking, stooping, and handling materials. This score is high for the occupations that conduct complex manual activities such as Choreographers, Physical Therapist Assistants, and Stonemasons, and low for the occupations such as Judicial Law Clerks, and Data Warehousing Specialists in O*NET database. As our theoretical construct is related to the intensity of the complex manual task, I use the importance score as the proxy for the intensity of the complex manual task.

I include several control variables to control other occupational characteristics related with urban agglomeration. I include the amount of annual wage since annual wage is known to be associated with the degree of urban agglomeration (Florida 2017; Glaeser and Resseger 2010). I also include occupational characteristics related work activities such as importance score for information recording task, analyzing task, and operating task to control the occupational characteristics affecting the coordination costs. In addition, I also include occupational characteristics related with transportation costs such as importance score for walking to workplaces, and indoor activity. The wage variable is measured by the annual wage of each occupation at the national level from the OES database. The variable is deflated using consumer price index (base year: 2012). The importance of related work activities from the work activity descriptor section of the O*NET database. The variables for occupational characteristics related with transportation costs are from work context descriptor section of O*NET database.

The definitions of the variables are shown in Table 12.

Table 12. Variable Description		
Variable	Notation	Description
Urban Agglomeration	Urb_{it}	The degree of urban agglomeration of occupation i in year t is measured by the proportion of the employment of the occupation in MSAs. The range is 0 – 1.
IT	IT_{it}	IT variable of occupation i in year t is measured by the level measure of "Interacting with Computer Work Activity" descriptor in O*NET Database. The range is 0 – 7. Level measure is defined as the degree to which the descriptor is required to perform their jobs.
Complex Communication Task Intensity	Com_{it}	Complex Communication Task Intensity of occupation i in year t is measured by the importance score of "Interpreting the Meaning of Information for Others" work activity descriptor in O*NET Database. The range is 0 – 5. The work activity is defined as "Translating or explaining what information means and how it can be used." in the O*NET database.
Complex Manual Task Intensity	$Manual_{it}$	Complex Manual Task Intensity of occupation i in year t is measured by the importance score of

		"Performing General Physical Activities" work context descriptors in O*NET Database. The range is 0 – 5. I is defined as "Performing physical activities that require considerable use of your arms and legs and moving your whole body, such as climbing, lifting, balancing, walking, stooping, and handling materials" in the O*NET database.
Annual Wage	$Wage_{it}$	Annual Wage of an occupation i in the year t is measured by the national estimates of annual wages in OES Database. It is adjusted by 2012 price level and divided by $10,000.
Recording Task Intensity	$Record_{it}$	Recording Task Intensity of occupation i in year t is measured by the importance score of "Documenting/Recording Information" work activity descriptor in O*NET Database. The range is 0 – 5. The work activity is defined as "Entering, transcribing, recording, storing, or maintaining information in written or electronic/magnetic form" in the database.
Analyzing Task Intensity	Ana_{it}	Analyzing Task Intensity of occupation i in year t is measured by the importance score of "Analyzing Data or Information" work activity descriptor in

		O*NET Database. The range is 0 – 5. The work activity is defined as “Identifying the underlying principles, reasons, or facts of information by breaking down information or data into separate parts.”
Operating Task Intensity	$Oper_{it}$	Operating Task Intensity of occupation i in year t is measured by the importance score of “Controlling Machines and Processes” work activity descriptor in O*NET Database. The range is 0 – 5. The work activity is defined as “Using either control mechanisms or direct physical activity to operate machines or processes (not including computers or vehicles).”
Walking Intensity	$Walk_{it}$	Walking Intensity of occupation i in year t is measured by the importance score of “Spend Time Walking and Running” work context descriptor in O*NET Database. The range is 0 – 5. The work context is defined as “How much does this job require walking and running?” in the database.
Indoor Activity Intensity	$Indoor_{it}$	Indoor Activity Intensity of occupation i in year t is measured by the importance score of “How often does this job require working indoors in

		environmentally controlled conditions?" work context descriptor in O*NET Database. The range is 0 – 5. The work context is defined as "How often does this job require working indoors in environmentally controlled conditions?" in the database.

5.3. Descriptive Statistics

Table 13 presents the descriptive statistics for our variables.

Table 13. Descriptive Statistics and Correlation Matrix

Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10
1. Urban Agglomeration	0.66	0.23	0.00	0.97	1.00									
2. IT	2.32	1.39	0.00	6.50	0.29 ***	1.00								
3. Complex Communication Task Intensity	3.18	0.69	1.00	4.87	0.08 ***	0.60 ***	1.00							
4. Complex Manual Task Intensity	2.83	0.91	1.04	4.90	-0.24 ***	-0.57 ***	- 0.47 ***	1.00						
5. Annual Wage	51.23	29.64	12.66	232.83	0.07 ***	0.55 ***	0.58 ***	-0.41 ***	1.00					
6. Recording Task Intensity	3.46	0.73	1.07	4.94	0.07 ***	0.53 ***	0.67 ***	-0.31 ***	0.40 ***	1.00				
7. Analyzing Task Intensity	3.28	0.74	1.23	4.94	0.07 ***	0.66 ***	0.79 ***	-0.52 ***	0.64 ***	0.65 ***	1.00			
8. Operating Task Intensity	2.65	0.95	1.04	4.92	-0.27 ***	-0.39 ***	-0.43 ***	0.67 ***	- 0.26 ***	-0.27 ***	-0.33 ***	1.00		
9. Walking Intensity	2.54	0.76	1.02	4.82	-0.10 ***	-0.52 ***	-0.46 ***	0.75 ***	-0.43 ***	-0.34 ***	-0.51 ***	0.50 ***	1.00	
10. Indoor Activity Intensity	3.90	0.94	1.03	5.00	0.25 ***	0.51 ***	0.43 ***	-0.55 ***	0.34 ***	0.44 ***	0.43 ***	-0.47 ***	-0.46 ***	1.00

Notes: *p<0.10, **p<0.05, *** p<0.01; two-tailed tests.

5.4. Empirical Specification

I estimate the following two-way fixed model specification (occupational – time fixed effects), where *i* indicates occupation, and *t* denotes year. I lag the IT variable by one year to address the simultaneity issue and account for the lagged effect of IT. $Control_{it}$ is to represent the control variables in the specification. Occ_i is to control unobserved occupation specific effect. D_t is the time-group indicator to control unobserved time specific effect. ϵ_{it} is an error term assumed to be normally distributed with zero mean and constant variance.

$$Urb_{it} = IT_{it-1} + Com_{it} + Manual_{it} + Control_{it} + IT_{it-1} \times Com_{it} + IT_{it-1} \times Manual_{it} + Occ_i + D_t + \varepsilon_{it}$$

I first estimate the model without the interaction terms to examine the unconditional effect of IT on urban agglomeration (i.e., H1). Then, I re-estimate models with interactions term to examine the hypotheses on the moderating effects of for the relation between IT and urban agglomeration (i.e., H2, H3).

6. Results

6.1. IT and Urban Agglomeration

I estimated the fixed effect models to test the research hypotheses. The results in model (1) of Table 14 suggest that the overall average effect of IT on urban agglomeration is positive (β = 0.004, $p < 0.05$), thus supporting H1. A one-unit increase in IT (approximately 43% compared to its average value), of which the range is 0-7, is associated with a 0.4 % increase in the degree of urban agglomeration. This implies that workers using more IT tools and systems are more agglomerated in the urban area.

The results of estimating the interaction effects between IT and complex communication task intensity is presented in model (4). The positive and significant estimate of the interaction term involving IT and complex communication task intensity ($\beta = 0.007$, $p < 0.05$) suggests that complex communication task intensity positively moderate the relationship between IT and urban agglomeration. When IT variable is fixed, one unit increase (approximately 31% compared to its average value) in the complex communication task intensity, of which the range is 0-5, is associated with around 0.7 % increase in the urban agglomeration level. This implies that the effect of IT on urban deagglomeration is weaker for the occupations that complex communication task is important for their job. Therefore, H2 is also supported.

The estimated moderating effect of complex manual task intensity is presented in model (4). The positive and significant estimate of the interaction term involving IT and complex manual task intensity term ($\beta = 0.006$, $p < 0.01$) suggests that the effect of IT on urban agglomeration is stronger for the occupations conducting complex manual task. When IT variable is fixed, one unit increase in the complex manual task intensity is associated with around 0.6% increase in the degree of urban agglomeration. Hence, H3 is also supported from this analysis.

Table 14. The Impact of IT on Urban Agglomeration with Weight

Dependent Variable	**Urban Agglomeration**			
Model	**(1)**	**(2)**	**(3)**	**(4)**
IT	0.004 ** (0.002)	- 0.011 ** (0.006)	- 0.005 (0.005)	- 0.034 *** (0.010)
Complex Comunication task Intensity	- 0.003 (0.004)	- 0.012 *** (0.005)	- 0.004 (0.004)	- 0.018 *** (0.005)

Complex Manual Task Intensity	- 0.011 *** (0.004)	- 0.012 *** (0.004)	- 0.017 *** (0.005)	- 0.023 *** (0.005)
Annual Wage	0.000 (0.000)	0.000 (0.000)	0.000 * (0.000)	0.000 (0.000)
Recording Task Intensity	0.001 (0.003)	0.001 (0.003)	0.007 (0.003)	0.001 (0.003)
Analyzing Task Intensity	- 0.001 (0.004)	-0.001 (0.004)	0.000 (0.004)	0.001 (0.003)
Operating Task Intensity	0.009 ** (0.003)	0.009 ** (0.003)	0.008 ** (0.003)	0.008 ** (0.003)
Walking Intensity	- 0.002 (0.004)	- 0.001 (0.003)	- 0.003 (0.004)	- 0.002 (0.002)
Indoor Activity Intensity	0.004 * (0.002)	0.005 * (0.002)	0.005 * (0.003)	0.005 ** (0.002)
IT × Complex Comunication Task Intensity		0.005 *** (0.002)		0.007 *** (0.002)
IT × Complex Manual Task Intensity			0.004 ** (0.002)	0.006 *** (0.002)
Constant	0.808 *** (0.025)	0.841 *** (0.026)	0.829 *** (0.025)	0.889 *** (0.030)
R-Squared	0.946	0.946	0.946	0.947
F-Statistics (Degree of Freedom)	2.77 F (9, 1293)	3.14 F (10, 1292)	2.91 F (10, 1292)	3.49 F (11, 1291)
Observations/ Groups	1974/16	1974/16	1974/16	1974/16
Notes: *p<0.10, **p<0.05, *** p<0.01; two-tailed tests. Robust standard errors are in parentheses. The unit of wage is ten thousand dollars.				

7. Additional Analysis

7.1. Sensitivity Analysis for the size of urban areas

To see how the relation between IT and urban agglomeration is changed by the size of areas, I conducted the same analysis for the degrees of urban agglomeration calculated for MSAs larger than top 20%, 50%, and 80% population size for each year. The estimated effect sizes for the main impact of IT on urban agglomeration, and the moderating effects of complex communication task intensity and complex manual task intensity are generally increasing as the scope of MSAs is broadening from top 20% MSAs to all MSAs. The results are presented in Table 15.

While the results of model (1) in Table 4 suggest that the average effect of IT on urban agglomeration is insignificant top 20% MSAs ($\beta = 0.000$, $p > 0.10$), the effects are significantly positive for top 50% MSAs ($\beta = 0.001$, $p < 0.01$) in model (3) and top 80% MSAs ($\beta = 0.002$, $p < 0.05$) in model (5). A one-unit increase in IT is respectively associated with 0.1% and 0.2% increases in the degree of urban agglomeration. Since the estimated effect of IT on urban agglomeration is 0.004 for all MSAs, the effect sizes are decreasing as the scope of urban areas is extending from top 20% to all MSAs.

The results of estimating the interaction effects between IT and complex communication task intensity is presented in model (2), model (4), and model (6). The positive and significant estimate of the interaction term involving IT and complex communication task intensity ($\beta = 0.001$, $p < 0.10$) in model (2), ($\beta = 0.002$, $p < 0.05$) in model (4), and ($\beta = 0.004$, $p < 0.05$) in model (6) suggests that complex communication task intensity positively moderate the relationship between IT and urban agglomeration respectively for top 20% MSAs, top 50% MSAs, and top 80% MSAs. Considering the effect is 0.004 for all MSAs in the main analysis, presented in model (3) in Table 3, the sizes of the effects are increasing as the scope of MSAs increasing from top 20% to all MSAs.

The results of estimating the moderating effect of complex manual task intensity are presented in model (2), (4), and (6). The positive and insignificant estimate of the interaction term involving IT and complex manual task intensity in model (2) ($\beta = 0.000$, $p > 0.10$) suggests that the effect is not clear for top 20% MSAs. However, the effect sizes are positive and significant for top 50% MSAs ($\beta = 0.001$, $p < 0.10$) and top 80% MSAs ($\beta = 0.002$, $p < 0.10$), which implies that the effects are stronger for conducting complex manual tasks for top 50% MSAs and top 80% MSAs. Considering effect size in the main analysis for all MSAs (β = 0.005, p < 0.10), presented in model (3) in Table 3, is larger than those effects for top 20% MSAs, and top 80% MSAs, the sizes of the effects are increasing as the scope of MSAs is broadened from top 20% to all MSAs.

Table 15. The Impact of IT on Urban Agglomeration for Top MSAs with Weight

Dependent Variable	**Urban Agglomeration (20%)**		**Urban Agglomeration (50%)**		**Urban Agglomeration (80%)**	
Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
IT	0.000 (0.000)	- 0.002 *** (0.001)	0.001 *** (0.000)	- 0.008 *** (0.002)	0.002 ** (0.000)	- 0.016 *** (0.004)
Complex Communication task Intensity	0.000 (0.000)	- 0.001 ** (0.000)	0.001 (0.001)	- 0.003 ** (0.001)	0.002 (0.002)	- 0.006 ** (0.003)
Complex Manual Task Intensity	0.000 (0.000)	- 0.001 * (0.000)	- 0.002 (0.001)	- 0.005 *** (0.001)	- 0.006 *** (0.002)	- 0.011 *** (0.003)
Annual Wage	0.000 ** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	- 0.000 (0.000)
Recording Task Intensity	- 0.000 (0.000)	- 0.004 (0.004)	- 0.002 (0.001)	- 0.002 ** (0.001)	- 0.003 (0.002)	- 0.003 (0.002)
Analyzing Task Intensity	- 0.000 (0.000)	0.000 (0.004)	- 0.000 (0.001)	- 0.000 (0.001)	0.003 (0.002)	0.001 (0.002)
Operating Task Intensity	0.000 (0.000)	0.004 (0.003)	0.003 *** (0.001)	0.003 *** (0.001)	0.006 *** (0.002)	0.006 *** (0.002)
Walking Intensity	0.000 (0.000)	0.001 (0.000)	0.002 * (0.001)	0.002 ** (0.001)	0.003 (0.002)	0.003 (0.003)
Indoor Activity Intensity	0.001 * (0.000)	0.001 * (0.000)	0.001 (0.001)	0.001 * (0.001)	0.002 (0.002)	0.003 (0.002)
IT × Complex Communication Task Intensity		0.001 *** (0.000)		0.002 *** (0.000)		0.004 *** (0.001)
IT × Complex Manual Task Intensity		0.000 (0.000)		0.001 *** (0.000)		0.002 ** (0.000)
Constant	0.014 *** (0.003)	0.019 *** (0.003)	0.059 *** (0.007)	0.078 *** (0.007)	0.203 *** (0.016)	0.241 *** (0.018)
R-Squared	0.944	0.946	0.965	0.967	0.959	0.960

F-Statistics (Degree of Freedom)	0.89 *F* (9, 1293)	2.51 *F* (11, 1291)	3.01 *F* (9, 1293)	5.29 F (11, 1291)	2.34 *F* (9, 1293)	3.09 F (11, 1291)
Observations/ Groups	1974/16	1974/16	1974/16	1974/16	1974/16	1974/16
Notes: *p<0.10, **p<0.05, *** p<0.01; two-tailed tests. Robust standard errors are in parentheses. The unit of wage is ten thousand dollars.						

7.2. Addressing Endogeneity with Instrumental Variable Approach

To address potential endogeneity due to omitted variables and reverse causality, I employ an instrumental variable (IV) approach by instrumenting individual occupation's (e.g., Operation Manager) IT usage with the other occupations' IT usage in the same aggregated occupation group (e.g., Managerial occupations) except for the focal occupation. A valid IV correlates with the endogenous variable (in our case IT variable) but does not correlate with the dependent variable (the degree of urban agglomeration). The logic behind this IV is that same occupational groups can have a similar tendency to use IT because people of the same occupational group conduct similar types of work. Therefore, there is a strong correlation between IV and the endogenous IT usage variable. On the other had, IT usage of the other occupation in the same occupational group should not strongly related with the focal occupation's omitted variables, and the dependent variable, because the aggregated IT usage variable of other occupations does not directly affect the occupational characteristics of the focal occupation. I used the minor level occupational group of the SOC system, which is the second broadest occupational group system in the system (see e.g., SOCPC (2020) for further discussion). Some minor occupational groups at a specific year contain only a single observation, our IV cannot be derived for those observations. I excluded these observations, and the sample for the IV analysis contains 1,451 year-occupation specific observations.

To test the validity of our IV analysis, I conducted under-identification of the instrumental variable whether the excluded instrument is correlated with endogenous IT variable. I employed Kleibergen and Paap (2006) rk LM statistics, and it reject the null hypothesis ($F = 16.078$, $p < 0.01$), which indicate that the IV is correlated with the endogenous IT variable. In addition, I conducted weak identification test using Cragg-Donald Wald F-statistics to check whether our IV is weakly correlated with IT variable. The test statistic is 24.964 which is above the critical threshold value proposed by Stock and Yogo (2005), 13.43 for 10% maximal IV size, indicating the alleviation of concerns regarding weak instruments.

The results in Table 6 suggest that our main analysis is qualitatively robust for the endogeneity issue. The overall effect of IT on urban agglomeration in Model (1) is positive ($\beta = 0.021$, $p < 0.05$), thus supporting H1. The interaction terms between IT variable and two moderating factors (Complex Communication Task Intensity, Complex Manual Task Intensity) in Model (4) are significantly positive, respectively ($\beta = 0.011$, $p < 0.05$) and ($\beta = 0.013$, $p < 0.01$). Hence, H2 and H3 are also supported. Therefore, this IV analysis support for the robustness of our main analysis, even though it cannot fully address the endogeneity concerns.

Table 16. The Impact of IT on Urban Agglomeration with Weight (IV Analysis)

Dependent Variable	**Urban Agglomeration**			
Model	**(1)**	**(2)**	**(3)**	**(4)**
IT (IV)	0.021 ** (0.010)	- 0.011 (0.019)	- 0.003 (0.012)	- 0.049 ** (0.022)
Complex Communication Task Intensity	- 0.009 (0.006)	- 0.022 ** (0.008)	- 0.012 (0.008)	- 0.030 *** (0.010)
Complex Manual Task Intensity	- 0.012 ** (0.006)	- 0.012 ** (0.006)	- 0.035 *** (0.012)	- 0.037 *** (0.011)
Annual Wage	0.000 *** (0.000)	0.001 *** (0.000)	0.001 *** (0.000)	0.001 *** (0.000)
Recording Task Intensity	0.007 (0.003)	0.006 (0.006)	0.006 (0.006)	0.004 (0.006)
Analyzing Task Intensity	- 0.003 (0.006)	- 0.004 (0.006)	- 0.002 (0.007)	- 0.001 (0.006)

Operating Task Intensity	0.014 ** (0.003)	0.014 ** (0.005)	0.013 ** (0.006)	0.012 ** (0.006)
Walking Intensity	- 0.000 (0.006)	0.001 (0.005)	- 0.002 (0.007)	- 0.003 (0.006)
Indoor Activity Intensity	0.004 (0.005)	0.005 (0.004)	0.004 (0.006)	0.004 (0.005)
IT × Complex Communication Task Intensity		0.008 *** (0.004)		0.011 ** (0.004)
IT × Complex Manual Task Intensity			0.011 ** (0.005)	0.013 *** (0.004)
Root MSE	0.034	0.034	0.035	0.034
F-Statistics (Degree of Freedom)	3.16 F (9, 910)	3.95 F (10, 909)	2.73 F (10, 909)	3.64 F (11, 908)
Observations/ Groups	1451/16	1451/16	1451/16	1451/16
Notes: *p<0.10, **p<0.05, *** p<0.01; two-tailed tests. Robust standard errors are in parentheses. The unit of wage is ten thousand dollars.				

8. Discussion and Conclusion

8.1. Discussion of Key Findings

Our findings are consistent with our theoretical arguments and hypotheses. First, I found that use of IT has a significant and positive association with the tendency of occupations to cluster in urban areas. This means that as IT usage in an occupation increases, measured by the intensity of computer usage, the occupation is more likely to be located in urban areas. Given that the main benefit of urban areas is to provide physical proximity among workers (Becker and Murphy 1992; Duranton and Puga 2004), the positive association implies that IT complements physical proximity in the urban areas rather than fully substituting for it, which is a consistent with the arguments in the previous research on the relationship between IT and physical proximity in the context of organization (Blinder 2009; Mithas and Whitaker 2007) or urban agglomeration (Gaspar and Glaeser 1998; Leamer and Storper 2001).

Second, I also found that the positive effects of IT on urban agglomeration are stronger for the workers requiring much complex communication tasks. This means that at a given level of IT usage, the tendency to locate in urban areas is stronger for workers requiring more complex communication task. As IT network does not fully substitute the role of urban areas to coordinate the complex communication task because some parts of complex communication task requiring tacit knowledge are hard to be coordinated by IT network (Autor et al. 2003; Mithas and Whitaker 2007), the positive moderating effects supports our argument that IT usage facilitates the urban agglomeration of the workers conducting the tasks of which coordination cannot be substituted by IT.

Lastly, I found that the positive effect of IT on urban agglomeration is stronger for the workers conducting more complex manual tasks. This means that at a given level of IT usage, the tendency to locate in urban areas is stronger for workers requiring more complex communication. Like complex communication tasks, IT cannot fully substitute the role of urban areas to coordinate the complex manual tasks given that IT network cannot effectively reduce the transportation costs required to coordinate such complex manual tasks. Therefore, the positive moderation effect of the complex manual tasks on the relation between IT and urban agglomeration indicates that the relation is adjusted by the capability of IT to substitute for the role of coordination of the urban areas.

9. Contributions

This study makes several contributions. First, our study offers new occupational level evidence supporting the complementary relationship between IT and physical proximity, and how such relation is moderated by the nature of task, in the urban agglomeration context. Although there are a number of empirical studies on the complementary between IT and physical proximity, they are mostly at the organizational level and/or in the offshoring context (Acemoglu and Autor 2011; Blinder 2009; Mani et al. 2014; Mithas and Whitaker 2007). In the urban agglomeration context, there has been little empirical evidence regarding the relationship between IT and physical proximity and how such relationship is adjusted by workers' task (Autor 2019; Gaspar and Glaeser 1998; Leamer and Storper 2014). This study contributes to the previous literature by providing such empirical evidence.

Second, this study extends previous studies in IS and economics on how IT changes the nature of work (Acemoglu and Restrepo 2018; Autor 2019; Autor et al. 2003; Lin 2011). Although previous studies analyzed that IT would increase the complexity of work, it does not study how such increase in the complexity of work would affect the urban agglomeration phenomena or the geographical distribution of workers. Therefore, our study contributes to the literature on the future of work, specifically, regarding how locations of work are influenced by IT usage and the changes in the nature of their work.

Lastly, our finding about the positive effect of IT on urban agglomeration would contribute for organizational designers and policy makers to geographically organize the workers to complement the digital transformation. Especially, our findings about the moderating factors, complex communication task intensity and complex manual task intensity, indicate that they should consider many occupational factors related to the substitutability of IT for the role of urban areas in coordinating workers' tasks.

10. Limitations and Future Research

This study is not without limitations. First, although this research theoretically argues for a causal effect of IT on urban agglomeration, I cannot claim causality for our findings due to potential endogeneity. For example, while IT can create complex tasks for high skilled workers

(Acemoglu and Restrepo 2018), it is also possible for them to use more IT to carry out complex tasks. Although I use an IV approach to address the potential endogeneity concern, our empirical approach does not allow us to perfectly identify the causal effect from IT to urban agglomeration. This would be further addressed by utilizing more empirical data which allow us to use natural experiment setting.

Second, although there are many different types of cities that vary in terms of infrastructure or geographical locations, I do not consider such heterogeneity across urban areas. For example, seaport cities help to transport a massive number of physical products to the other countries, while cities with international airports enable cognitive workers to easily travel and interact with one another through air transportation. Examining how IT has changed the demand for different types of urban areas would be an interesting avenue for future research. Such an analysis will provide guidance regarding how to devise regional development strategies and geographical human resource allocation strategies along with the increased use of IT.

Third, our study is based on data prior to COVID-19 pandemic. While the pandemic has accelerated the adoption of IT-based remote working practices, our data does not capture such improvement in IT that substituted for physical proximity during the pandemic. However, the pandemic may actually confound the estimation of the impact of IT on urban agglomeration since the pandemic also facilitates deagglomeration (i.e., people move away from urban areas to avoid contagion). Nevertheless, examining the implications of the pandemic regarding the relationship between IT and urban agglomeration, and the nature of work more broadly, would be an interesting avenue for future research.[4]

[4] Recent studies suggest that COVID-19 has had a significant impact on where people work. For example, Brynjolfsson et al. (2020) analyzed a series of surveys collected at the early stage of the pandemic, and found that around 35% of workers started to work from home since the beginning of the pandemic. Other studies examined productivity implications of the increased IT-

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based remote work due to COVID-19. For instance, Bartik et al. (2020) reported conflicting findings from two firm-level surveys about the productivity impact of remote work. While one survey found little productivity loss due to remote work, the other survey with a larger sample reported significant productivity loss due to remote working although about 30% of workers reported that they are more productive by staying home (for highly educated workers or workers with prior experience with remote work). A recent study on the productivity implication using more granular data presented detailed patterns of productivity loss from remote work (Gibbs et al. 2021). They analyzed observational data of 10,000 professionals at a large Asian IT services company, and found that remote work resulted in 8-10% productivity loss, mostly due to increased time spent on communication and coordination. These studies indicate that the current IT and remote working practices might not be able to substitute for the physical proximity that urban areas provide for workers. Similarly, Florida et al. (2021) maintained that large cities would not lose but transform their roles after the pandemic.

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DISCUSSION AND CONCLUSION

Discussion of Key Findings

This dissertation developed a theoretical framework that considers both positive and negative relationships between IT and coordination costs: while IT usage can increase the degree of specialization and decrease the degree of urban agglomeration by reducing the coordination costs in the division of labor system, IT usage can also decrease the degree of specialization and increase the degree of urban agglomeration by increasing the coordination costs. While previous studies on the relationship between IT and coordination have mainly focused on the positive effect of IT (e.g., by reducing the costs for sharing information) (Brynjolfsson et al. 1994b; Gurbaxani and Whang 1991; Ray et al. 2013), the SBTC literature (Acemoglu and Autor 2011; Autor et al. 2003; Bresnahan et al. 2002; Tambe and Hitt 2012) suggests that IT usage might increase the coordination costs by making tasks performed by workers more complex such that they require more information exchange. This dissertation aimed to investigate those two countervailing impacts of IT on coordination costs by examining two specific aspects of work related to the coordination costs: the degree of specialization and the degree of urban agglomeration,

Empirically, I presented evidence that IT usage facilitates specialization and urban agglomeration. In addition, I found that workers' cognitive skill level and the degree of urban agglomeration positively moderate the relationship between IT usage and specialization, and that the intensity of complex communication task and the intensity of complex manual task positively moderate the relationship between IT usage and urban agglomeration. These findings provide us the following implications regarding the impact of IT usage on coordination.

First, my dissertation provides empirical evidence that implies both positive and negative effects of IT on coordination costs. Given that specialization is determined by the division of labor among co-workers, the size of the coordination costs for the division of labor is a key determinant of the degree of specialization (Becker and Murphy 1992). Therefore, the positive effects of IT usage on specialization found in the first essay imply that IT improves coordination of tasks among workers more than that within a worker. This finding also implies that IT can improve coordination by reducing the costs for monitoring, contracting, and communicating among workers, thereby resulting in more remote working and outsourcing. The improved coordination in turn further advances the division of labor and increases the degree of specialization.

On the other hand, the positive effect of IT usage on urban agglomeration found in the second essay implies that IT increases the coordination costs by making tasks more complex such that they require more coordination and information exchange. Because the degree of urban agglomeration is determined by the trade-off between the low coordination costs and the high living costs in urban areas (Duranton and Puga 2015), the positive effect of IT usage on the degree of urban agglomeration implies that IT usage would increase the coordination costs, which increase the need for physical proximity provided by urban areas. This increase in coordination costs due to IT can be explained by the SBTC literature that IT makes workers' tasks more complex such that more information (especially tacit knowledge) exchange is required (Acemoglu and Autor 2011; Acemoglu and Restrepo 2018; Autor et al. 2003; Spitz-Oener 2006; Tambe and Hitt 2012). Indeed, previous studies in SBTC found that IT usage or IT offshoring have increased the amount of complex cognitive tasks that require more information and complex communication for information sharing and exchange. Based on the previous literature, the positive effect of IT usage on urban agglomeration I found can be interpreted as IT increasing coordination costs by making users' tasks more complex.

Therefore, the positive effects of IT usage on specialization and urban agglomeration imply that IT usage can either increase or decrease the coordination costs depending on the context. Although the findings are from different contexts, that is, specialization and urban agglomeration, they provide evidence of the double-edged nature of IT with respect to its impact on coordination costs.

Second, while this dissertation presented seemingly contradictory evidence about the relationship between IT usage and coordination, a potential explanation is that the urban agglomeration (or physical proximity in general) plays a role as a positive mediator for the relationship between IT usage and coordination. Because IT usage facilitates urban agglomeration which results in a reduction of coordination costs, the negative effect of IT usage on coordination costs would be weakened by urban agglomeration.

This conjecture is supported by the negative main effect of IT usage on specialization of Model (3) in Table 5. After including the moderating effect of urban agglomeration, we found that the direct relationship between IT usage and the degree of specialization becomes negative ($\beta = -0.030$, $p < 0.01$), which implies that IT usage increases the degree of specialization (or decreases coordination costs) for workers with high degree of urban agglomeration, but not for those with relatively lower degree of urban agglomeration. This implies that urban agglomeration weakens the negative effect of IT usage on coordination costs. Although this explanation is preliminary and we need more thorough investigation on the role of urban agglomeration in the IT-coordination costs relationship, this dissertation provides a direction for future research for understanding how IT affects coordination (and costs) and the role of physical proximity in the underlying mechanism.

Conclusion

In conclusion, this dissertation examined the impacts of IT usage on two aspects of work related to coordination costs: the degree of specialization and the degree of urban agglomeration. By doing so, this dissertation examined the double-edged nature of the effect of IT on coordination costs.

In the first essay, I proposed a theoretical framework on how the degree of specialization is determined by coordination costs and argued that IT usage can both increase and decrease the degree of specialization by building on the coordination perspective and the SBTC literature. By analyzing the US occupational data, I found evidence of the positive impact of IT usage on the degree of specialization and the positive moderating effects of cognitive skill level and the degree of urban agglomeration on the relationship between IT usage and the degree of specialization. This study contributes to the literature on specialization by enhancing our understanding of how IT affects the degree of specialization, which is an important aspect of work, and by suggesting moderating factors for the relationship. In addition, this study provides important guidance for organizational designers regarding how to adjust the size of task scope of workers when the organization is digitally transformed.

In the second essay, I proposed a theoretical framework on how the degree of urban agglomeration is determined by coordination costs and argued that IT usage can both increase and decrease the degree of urban agglomeration. Using occupation-level data from the U.S., I found that IT usage positively affects the degree of urban agglomeration, and this relationship is positively moderated by complex communication task intensity and complex manual task intensity. This study contributes to the literature about the relationship between IT and urban agglomeration by providing a new body of evidence based on occupational level data, supporting the complementary relationship between IT and physical proximity, and how such relation is moderated by the nature of task, in the urban agglomeration context.

In addition, the findings from this dissertation contribute to the literature on the impact of IT on coordination costs by providing empirical evidence supporting both positive and negative effects of IT usage on coordination costs. While previous literature about the impact of IT on coordination costs generally focuses on the negative mechanism such as reduction of the costs for exchanging information, the findings from the SBTC literature suggests that IT usage might increase coordination costs by making tasks more complex. Because the positive effect of IT on specialization from the first essay can be interpreted as the negative effect of IT on coordination costs, and the positive effect of IT on urban agglomeration can be interpreted as the positive effect of IT on coordination costs, this dissertation provides a body of evidence for both directions, thereby shedding new light on the double-edged nature of IT with respect to influencing coordination costs. Furthermore, this study provides preliminary but important insights regarding the role of urban agglomeration in understanding when IT usage can reduce coordination costs. In summary, these two essays in this dissertation can serve as a foundation for future research on the impact of IT on coordination.

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