THE LONDON SCHOOL OF ECONOMICS
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ESSAYS ON TASKS, TECHNOLOGY, AND TRENDS IN THE LABOR MARKET

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DECLARATION

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ABSTRACT

This thesis contains three essays on the role of tasks and technology in explaining the trends in reallocation of employment across occupations and sectors, and inequalities in the labor market.

The first two chapters focus on the task content of occupations with special emphasis on the effect of interpersonal interactions in the changing structure of employment in the labor market. Chapter 1 studies structural change of employment at the task level. Interactions with customers are a key friction against the implementation of potentially better production styles and technologies, since customers are hard to train and should be satisfied according to their tastes. Using a wide range of data sources on tasks, detailed occupation employment, labor productivity, and computer adoption, Chapter 1 develops a novel task measure, interpersonal-service task intensity, to study the growing importance of service activity in the US labor market in recent decades and explores its linkages with technical change. The chapter explains the empirical findings with a model of structural change at the task level which suggests two distinct roles for interpersonal-service intensity and task-routinizability.

Concerned with the reallocation of employment jointly across occupations and sectors, Chapter 2 quantifies the impact of interpersonal-service task intensity and routinization on job polarization and structural change of sector employment. I estimate a task-biased technical change model which is capable to address occupation-specific and sector-specific technical change separately and show that substantial portion of occupational and sectoral employment reallocation between 1987 and 2014 in the US can be explained by the two task aspects. While both types of tasks are significant drivers of job polarization, interpersonal-service tasks stand out in explaining the growth of service sector employment. Using the framework I also suggest answers to several issues in the related literature.

Chapter 3 switches the focus of study from the task content to skills while keeping the occupation-based perspective. The last chapter studies the importance of within-occupation heterogeneity of skills in understanding the rising labor market

inequalities. I document that employment and wage growth of occupations tend to increase monotonically with various measures of skill intensity since 1980 in the US, in contrast to the existing interpretation of labor market polarization along occupational wages. I establish robustness of the documented fact, explore the sources of the seemingly contrasting finding and argue that labor market polarization cannot be interpreted as polarization of skills that are comparable across occupations. The chapter reconciles the documented facts in an extended version of the canonical skill-biased technical change model which incorporates many occupations and within-occupation heterogeneity of skill types.

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Chapter 1

INTERPERSONAL-SERVICE TASKS AND THE OCCUPATIONAL STRUCTURAL CHANGE

The rise of service economy is a constant of modern economic growth. This chapter takes a task-based perspective on the growth of services. Customers are inseparable from the production of interpersonal-service tasks and retard the productivity growth through their preferences and own capabilities. Customers, unlike workers, are hard to train and direct; and any change in the production process to increase efficiency potentially disturbs customer satisfaction. I document that the key task aspect characterizing service sector specialization of occupations is interpersonal interactions with customers (interpersonal-service tasks). The growth of occupation employment after 1970 in the US is strongly predicted by the interpersonal-service task intensity. The evidence suggests that interpersonal-service task content is associated with slower labor productivity growth while it is not related to computer adoption that revolutionized the workplace in recent decades. I reconcile the empirical findings of the chapter in a model of occupation-based structural change with two distinct channels of technology where interpersonal-service task intensity of occupations is linked to slower occupation-specific technical change, and routinizability leads to deepening of ICT capital.

1.1 Introduction

Modern economic development is attached to the rising importance of services in the economy and particularly in the labor market, where this transformation can be seen in great detail. It is well documented that employment has been reallocated into the broad service sector, more detailed service producing industries, and even into occupations which are relatively specialized in service production.[1] The leading technology based explanation for the rise of services has been their relatively low levels of productivity growth.[2] Particular emphasis since the early studies on the service economy has been placed on the presence of customers during the production process, which potentially leads to slower productivity growth in two ways. First, an improvement in the efficiency of production is subject to customers' approval (Baumol, 1967). Second, customers influence the efficiency of output also with their own skills (Fuchs, 1968).[3] Despite this clear stress on the task content, the literature lacks evidence linking structural change to task attributes.

In this paper, I provide a wide-ranging analysis of tasks that are defined by interactions of workers with outside of the firm, which I dub interpersonal-service tasks, in the US labor market in recent decades.[4] There are three contributions of this paper that shed light on the disaggregate characteristics of the increasing importance of service activity in the labor market. First, I document for the first time that interpersonal-service tasks are in fact the key task aspect characterizing service sector employment. Second, I introduce evidence suggesting that interpersonal-service tasks can be considered as a distinct task attribute in comparison to other types of interactiveness, and other task aspects that are studied in the recent literature. Third, I provide novel evidence on the links of interpersonal-service tasks to the changing structure of oc-

1 Herrendorf, Rogerson, and Valentinyi (2014) provide a review on the literature on structural change as well as illustrating the stylized facts of structural change on sectors. See Duernecker and Herrendorf (2017) for the employment share growth of service occupations.

2 See Ngai and Pissarides (2007) and Acemoglu and Guerrieri (2008) for examples of technology based mechanisms. See Kongsamut, Rebelo, and Xie (2001) for an example of a mechanism based on preference and income effect

3 Although lower labor productivity growth in services is well known in the literature and widely used in models of structural change, its determinants are surprisingly understudied in the recent economics literature. An exception is Young (2014), who argues that slower service productivity growth can be driven by the reallocation of labor itself within a multisector Roy model framework.

4 In the terminology of this paper the term interpersonal-service tasks excludes service provision without interpersonal interactions, and interactions without service content. Here the service content is defined according to the existence of an actual customer.

cupation employment and technology, and explain them in a task-based model of structural change.

I take a technology-based perspective to explain the continuous rise of interpersonal-service intensive occupations. Interpersonal-service task intensity acts as an occupation-specific friction on productivity growth. This friction is inherent to the nature of interpersonal interactions with customers since customers are simultaneously the consumers of the service and an input of production. When interactions with customers are the core activity of a task, any reduction in a worker's time devoted to a customer as a result of the implementation of a better production style potentially disturbs the perceived quality by customer, hence customer satisfaction. Customers, unlike workers, are difficult to train and direct. Accordingly, complications arising from customers severely limit the capacity of firms in reflecting the existing economy-wide innovations as well as in the flexibility of managers in restructuring the workplace practices.[5] As long as occupations that perform different tasks are complements, relatively slower pace of technical change in interpersonal-service intensive occupations leads to increasing relative labor demand for interpersonal-service tasks.

Such frictions are effective regardless of whether the task is suited to routinization, a process which has been substituting routine labor on the back of falling computer prices (Autor, Levy, and Murnane, 2003). A care worker whose task is manual intensive is subject to similar levels of customer-driven barriers to efficiency compared to a doctor who is complemented by the use of better equipment, or to a sales worker whose job can be easily codified and partly replaced by computers. Consequently, differences in interpersonal-task intensity can help explain the changing relative demand between two occupations that share a similar level of routinizability.

Innovations in ICT mainly operate through the changing structure of capital, i.e. increasing use of computers in production, that can also decrease the demand for labor. On the other hand, customer interactions continue limiting productivity even when the task is highly computerized. Computerization has been extensively taking place in customer services thanks to automated response systems, in retail sales jobs following the increasing use of internet shopping, and in cashier jobs through self-service checkouts despite their high intensity in interpersonal-service tasks. While

5 The productivity challenges particular to services has been studied relatively more in management literature. Lovelock and Young (1979) provide several examples on how customers complicate switching to more productive service provision. Drucker (1991) and Van Biema and Greenwald (1996) argue that the productivity problem of services involve elements that go beyond the insufficiency of skills, capital intensity and investment.

it is true that these occupations are not among the fastest growing, an increasing employment demand for these jobs compared to other routinizable ones is at odds with what is expected from their automation experience. This is in sharp contrast with the remarkably falling demand for office and administrative support workers or machine operators whose tasks are also affected by computerization while involving low levels of service oriented interactions with customers.[6]

I begin the analysis by developing a one dimensional index of interpersonal-service task intensity (ITI) considering a large set of task characteristics from the O*NET database. The ITI index focuses on work context and activities rather than worker skills and abilities. The index measures the importance of interpersonal interactions with customers and not the complexity of the interactions.[7] The set of jobs with the highest ITI includes childcare and social workers, nurses, therapists, teachers, clergy, sales agents, and bartenders, all of which can be found throughout the skill and wage distribution of occupations.

Key in my classification of interpersonal tasks is the direction of interactions. As ITI is distinguished by interactions with the outside of the firm, I carefully compare it with its complement, interpersonal interactions within the firm. Although correlated due to common interactive content, the two task aspects exhibit notable differences. While ITI can explain service sector specialization of occupations remarkably well and does not show a significant association with skill intensity of occupations, I find that a similarly constructed measure of within-firm interactions intensity is not related to service specialization, monotonically increases with cognitive skill-intensity, and is most concentrated in high-wage occupations. In this sense, within-firm interactions fit very well into non-routine cognitive interpersonal task classification of Autor, Levy, and Murnane (2003).

Since this paper argues ITI as the task-level source of structural change, an important question is to find out whether ITI can be considered a distinct task aspect when compared with the existing task-based drivers of occupational reallocation of employment. Therefore, I compare ITI with other relevant task aspects relating to rou-

6 More precisely, from 1980 to 2000 customer service representatives, cashiers, and retail sales workers all increased their employment share that sums up to 2.2 percentage points. On the other hand, office clerks, sewing machine operators and shoe machine operators all experienced declining shares which totals 1.53 percentage points. Both group of occupations have been subject to intensive routinization but the former managed to grow in employment share.

7 For instance, sales jobs can be as interpersonal-service intensive as the tasks of architects working with clients, though the latter requires a superior level of interactive complexity.

tinization and offshoring hypotheses.[8] ITI appears to be negatively correlated with measures of routinizability and offshorability, but they are both conceptually and observationally distinct task attributes.

Routinizability is higher when the occupation's required set of tasks are more routine, less abstract and less manual intensive (Autor, Levy, and Murnane, 2003). Interpersonal-service tasks cover a wide range of activities that involve both routinizable and non-routinizable elements. Routine sales jobs, manual personal service jobs, and abstract professional jobs have above-average ITI scores. When it comes to offshorability the key concept is whether a service is delivered personally or impersonally (Blinder, 2009). ITI does not essentially belong to any of these sets. An example is helpline jobs in call centers. Although they perfectly fulfill the definition of an interpersonal-service task, they are actually among the most offshored services. On the other hand, many on-site jobs that can never be offshored have only little interpersonal-service content such as construction workers. I discuss in detail how these alternative task measures differ from ITI in the paper.

My analysis on the post-1970 US labor market reveals that ITI is closely connected to the changing structure of occupation employment. In particular, the economy has been steadily becoming more interpersonal-service intensive in contrast to slower and intermittent growth patterns observed for other task aspects. Between 1980 and 2010 ITI seems to be the leading task attribute that can explain the employment and wage bill growth of detailed occupations. Furthermore, I show that none of the alternative task attributes can overturn ITI's success.

The finding that places ITI as the most important driver of occupational employment trends is in line with the motivation of ITI as the source of slower productivity growth in services according to models of structural change (e.g., Ngai and Pissarides, 2007), however the exact link of ITI to productivity is obscure in the literature. Customer preferences and capabilities stressed by Baumol (1967) and Fuchs (1968) limit the set of innovations in the workplace that can be successfully applied. Customer-driven barriers may increase the cost of innovation and putting them into practice, acting as an occupation-specific brake on technology growth.[9] Alternatively, contexts

8 Routinization refers to decline in the labor demand in routine tasks as a result of increasing use of computers which efficiently performs codifiable tasks. Offshoring refers to relocation of task input from domestic labor market to other countries as a result of technology and globalization. See the literature review section below for more discussion and the references.

9 The case for jobs that require interactions within the firm is quite the opposite. The key distinction between within-firm and customer interactions is such that the former is easier to restructure while the latter is not. A manager can change the way people interact for work within the firm as well as its

that are intensive in interpersonal-service tasks could be inherently resistant to automation. In this case, the rise of high-ITI occupations would be driven by routinization.

The last empirical task of this paper is to explore ITI's connection with technology. Using BLS labor productivity data I observe association of ITI with slower industry labor productivity growth. Furthermore, using several indicators of ICT intensification at occupation, sector, and local labor market level I confirm that ITI is not central to routinization driven by increasing use of computers in the workplace, suggesting that the relative stagnancy in interpersonal-service intensive occupations does not stem from the changing structure of capital after computers.

I qualitatively explain the empirical findings of the paper in a model of structural change that occurs at the task level. In a framework involving several industries and occupations, occupation-specific technical change is assumed to be slower with ITI. Therefore with technological progress, labor productivity of interpersonal-service intensive production units grows slower while employment is reallocated into these industries and occupations if there is poor substitutability across tasks, and sectors. This aspect of the model can be seen as an extension of Ngai and Pissarides (2007) to include occupations. Following the literature, routinization is introduced in the model as decline in the price of ICT capital relative to other kinds of capital inputs. Occupational variation in the impact of routinization is given by occupation-specific shares of ICT capital in the task-capital. Consequently, ICT capital deepening and different ICT shares in occupations lead to a higher labor productivity growth and slower employment demand growth in production units that are more routinizable.[10]

The rest of the paper is organized as follows. I provide a review of the relevant literature in the next section. In Section 1.3, I introduce ITI index and study its properties in comparison with other relevant task characteristics. An analysis of ITI's impact on employment demand shifts is provided in Section 1.4, and on technical change in Section 1.5. In Section 1.6, I study an industry-occupation model of structural change that can explain the empirical observations of previous sections. Finally, Section 1.7 concludes the paper.

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intensity with great flexibility to boost performance. The workers are an input of production on the performance of whom the firm is primarily responsible. Given the importance of complementarities between management practices and different forms of technology (see e.g., Bloom, Sadun, and Van Reenen, 2010, for a review), the technological change has the potential to augment productivity in tasks where within-firm interactions are intense (see, e.g., Deming, 2015).

10 In this respect the model applies the idea of capital deepening and sector-specific capital shares as a source of structural transformation in Acemoglu and Guerrieri (2008) in the context of computerization.

1.2 Related Literature

The paper is connected to several strands of literature which are briefly reviewed in this section. The first set of papers are related in terms of how services are viewed with respect to employment growth and labor productivity. The motivation of ITI as the relevant metric of service activity in this sense can be found in the early work on service economy. In fact, discussions in the literature regarding the low productivity growth of services cluster around the lack of impersonal tasks in certain services. Fuchs (1968) stresses the importance of customer-worker interactions in the production process for understanding the service sector productivity. Baumol (1967) argues that the required modification in production style to increase efficiency may not be welcomed by the consumer whose satisfaction is not necessarily aligned with the efficiency of the production.[11] Independently, a similar theme is also discussed in the management literature. Lovelock and Young (1979) argue that customer acceptance is a key issue in productivity growth in services which introduces several barriers to implementation of the existing knowledge. The literature observes that the problem is inherent to the nature of service work, which involves great heterogeneity in terms of the tasks performed, rather than a matter of investment and allocating physical resources; and that the interpersonal element is an obstacle on productivity growth on managing a more productive service work (Van Biema and Greenwald, 1996). The relative stagnancy of service tasks persists despite the adoption of capital-augmenting technological development (Drucker, 1991; Van Biema and Greenwald, 1996). My results broadly support the insights of these papers on the service economy.

The paper also connects to the recent literature on services and reallocation of employment at occupation level. Barány and Siegel (2017) argue that labor market polarization stems from structural change mainly due to slower productivity growth in service sectors and service sector specialization intensity of jobs at the tails of wage distribution. Duernecker and Herrendorf (2017) take a slightly different view and emphasize the role of structural change at the level of occupations rather than sectors. While this paper shares the perspective of both papers on the key role of service activity, it is closer to the latter in assuming service-driven changes at occupation level.

11 In Baumol's words: *"A half hour horn quintet calls for the expenditure of 2 1/2 man hours in its performance, and any attempt to increase productivity here is likely to be viewed with concern by critics and audience alike."* (Baumol, 1967)

Different from Duernecker and Herrendorf (2017), I study a model extended to many sectors and occupations, and also allow for routine-biased technical change. Another key difference is that in this paper I emphasize the role of interpersonal-service tasks in characterizing the service content of an occupation or sector and thereby provide a continuous extension of the binary approach of these papers on service classification.

Another set of papers, those on routine-biased technical change and globalization, relate to this one mainly on two grounds. First, both include direct arguments on interpersonal interactions in the labor market. Second, they are suggested as significant drivers of occupational labor reallocation and it is of interest of this paper to see how the proposed channel of relative demand growth of this study compares to them.

Autor, Levy, and Murnane (2003) develop the framework of routinization where tasks are grouped in five categories: routine cognitive, non-routine cognitive, routine manual, non-routine manual, and non-routine interpersonal. The classification is designed to argue how recent technical advances in computers affect the task demand. Their interpersonal measure is closely related to hierarchical contexts within the firm where complex task requirements such as coordination, direction, and planning are required. In a related paper, Autor, Katz, and Kearney (2008) combine non-routine cognitive and non-routine interpersonal task aspects under the single title of abstract tasks. My contribution to this literature is that I find that the interpersonal task dimension these papers utilize is similar to within-firm interpersonal tasks, and that interpersonal-service task content, which is essentially characterized by interactions of workers with other parties outside the firm, is distinctly positioned in relation to routinizability. While computers cannot easily replace cognitive interpersonal tasks such as managing a firm or complex interactions among coworkers, its effect on interpersonal-service tasks is not straightforward. In fact, there are interpersonal-service intensive occupations that can be routinized (e.g. retail sales) as well as ones that are hard to be replaced by computers (e.g. care workers). Another contribution of this paper to this literature is showing that ITI is not associated to ICT intensity measures from several sources.

One exception in the routinization literature that uses an interpersonal task variable apart from cognitive interpersonal measure is Goos, Manning, and Salomons (2009). Similar to this paper Goos, Manning, and Salomons (2009) generate a variable to measure service tasks and assess how it relates to job growth. While there is some overlap between their service index and ITI, my paper differs in two aspects. First, they view service content as part of non-routinizable tasks and assign a role to service tasks similar to manual tasks while I emphasize that interpersonal-service tasks and elements of routinization hypothesis are distinct in several ways. Second, they find that their service task variable is not a significant source of occupational employment growth in Europe while this paper suggests that ITI plays a central role in explaining demand changes in the US.[12]

This paper is also related to the literature on routine-biased technical change hypothesis due to how routinization is modeled. I depart from the original Autor, Levy, and Murnane (2003) framework by assuming homogeneous labor skills in the production of tasks, and similar to Goos, Manning, and Salomons (2014) my modeling of routinization results in faster decline in occupation-specific cost of capital in more routinizable jobs. Furthermore, I contribute by endogenously having this result by assuming varying shares of ICT capital in the total capital used in task production of each occupation.

The literature on offshoring predicts outsourcing of certain tasks to other countries due to globalization and technological change (e.g., Blinder, 2009; Blinder and Krueger, 2013; Feenstra and Hanson, 1999; Grossman and Rossi-Hansberg, 2008; Jensen and Kletzer, 2010). The task characteristics that are correlated with offshorability of an occupation share interpersonal elements. In particular, it is argued in this strand of literature that the jobs that cannot be replaced by international trade are characterized by the need of material presence of the worker including some of the tasks with high ITI. However, my approach to interpersonal tasks is essentially distinct from that of papers on offshoring because high ITI occupations also include offshorable ones, and offhsorability of an occupation does not distinguish between interactions among coworkers or with customers. In addition my results confirm the finding in recent papers in task literature on the relatively minor role of offhsorability in explaining occupational employment demand changes (Autor and Dorn, 2013; Goos, Manning, and Salomons, 2014).

There is a growing interest on labor market implications of non-cognitive skills in general, and in particular several aspects of interpersonal skills in the economics

12 Michaels, Rauch, and Redding (2016) can be considered as another exception within the routinization framework that introduces additional interpersonal variables. They provide the most detailed and far-reaching inspection of tasks and technology using a methodology based on matching thesaurus verbal meaning categories to occupation definitions. They observe that metro areas are becoming increasingly specialized in interactive tasks. Their definition of interactive tasks may involve common elements with ITI such as intersocial volition division in Roget's Thesaurus. However, the interactiveness measure has no special emphasis to interactions with outside of the firm, making it hard to compare with ITI.

literature.[13] Finally, this paper is also related to the papers on the role of interpersonal tasks and skills in the labor market which are briefly reviewed below. A fundamental departure of my paper from those is that I solely focus on task heterogeneity and reallocation of employment while they study skill heterogeneity of workers as well as tasks and its implications on the labor market outcomes, particularly wages.

Borghans, Ter Weel, and Weinberg (2008) classify interpersonal interactions as *caring* and *directness*. The former is more important for teachers and nurses and the latter in sales jobs. They motivate this classification on the psychology and management literature on the grounds that these *styles* matter in effective communication. Rather than interpersonal styles, I focus on a particular direction of interactions with reference to the unit of production.

Deming (2015) studies a particular subset of interpersonal skills and argues that social skills are disproportionately rewarded in the high-skilled labor market as opposed to cognitive skills that do not require social skills. Social skills in the paper involve elements like negotiation, persuasion, coordination which require complex skills. The author particularly focuses on interactions within the firm. Consequently, the paper develops the importance of social interactions in a model of team-production where the complementarity of social and cognitive skills are emphasized. It is also pointed out in the paper that this task aspect is different from what he calls service tasks which is possibly related to ITI.

While the two papers mentioned above focus on specific types of interpersonal interactions depending on the context there are others which aim to combine all aspects of interpersonal tasks. Borghans, Ter Weel, and Weinberg (2014) develop a comprehensive interpersonal measure by combining *people* tasks from DOT to understand the impact of technology on the labor market outcomes of underrepresented groups. Postel-Vinay and Lise (2015) study multidimensional skills in relation to human capital and classify the tasks in three as cognitive, manual, and interpersonal. From O*NET the authors develop a measure of interpersonal interactions including all interpersonal task variables in O*NET. One of their key findings is that interpersonal task aspect is a distinct productive attribute in the labor market.

13 See Borghans et al. (2008) for a review.

1.3 The Interpersonal-Service Task Intensity Index

In this section I develop the ITI index and study its properties. In order to untangle the service-relevant task content, ITI emphasizes a particular direction regarding interpersonal interactions: those between workers and customers. Therefore in the following I introduce the ITI measure in contrast to interactions that take place within the firm. I also carefully evaluate how ITI compares to other interpersonal-related task aspects in the literature as well as skills.

The strategy I employ for selecting the types of interpersonal tasks is based on O*NET database which provides detailed task variables and is increasingly used in the existing task literature. The organization of O*NET database follows the content model which provides a rich and detailed set of occupational characteristics. The database includes a set of occupational content categories which contain several types of task information. Some content information is worker-oriented and includes worker characteristics, worker requirements, and experience requirements. These characterize the *people* in those occupations, and hence are relevant for studies on abilities, interests, values, styles, skills, education, experience and training. Others are job-oriented that reflect the character of occupations: occupational requirements, workforce characteristics, and occupation-specific information. Some of the O*NET task categories enable comparisons across occupations and some are occupation-specific.

The ITI index targets measuring the task characteristics that are related to the nature of the work in terms of interpersonal-interactions with outside of the firm rather than the skills of workers. It also aims to form a one-dimensional occupational index, and hence should be comparable across different occupations. Therefore in this paper I mainly focus on job-oriented and cross-occupation task characteristics of O*NET. This leaves me with task information on work activities and work context under the title of occupational requirements. Work activities include job behaviors that can be observed in many occupations. Work context contains factors that shape the nature of the work. Both include a variety of interpersonal task characteristics. The former has 17 variables titled *interacting with others* and the latter has 14 characteristics of i*nterpersonal relationships*.

Interpersonal Interactions, Service Activity, and Skills

The key to my classification of interpersonal tasks is the required direction of interactions for the performance of the task. Jobs may require their workers to interact with other parties outside the organization, while workers may be required to interact horizontally with peers, and vertically with supervisors and subordinates within the firm. Since not every interpersonal variable of O*NET is relevant in terms of my division of tasks, I select 7 to form the ITI index and another 7 to reflect within-firm interactions. The variables included in the two indexes are listed in Table 1.1. The excluded variables are those that are too general to indicate the direction of interaction such as contact with others, or face-to-face discussions; and those that are not directly relevant such as e-mail, telephone, monitoring and controlling resources.

I compute task score in two steps. First is the aggregation of scores at detailed O*NET SOC categories to a set of 322 consistent Census occupations based on the classification of Dorn (2009). I standardize each detailed task variable to have mean of 0 and standard deviation of 1.[14] Next, I calculate the mean across related task variables to calculate the two indexes for each occupation group, which is again standardized as explained above. The resulting measures for interpersonal-service tasks and within-firm interactions are positively correlated with an employment-weighted correlation coefficient of 0.46. This correlation is not unexpected as jobs may jointly require outside or within-firm interactions, and detailed task variables might imperfectly capture both types of interactions to some extent.

I start studying the comparative analysis of interpersonal tasks by showing in Table 1.A.1 the top and bottom ranked occupations for both of the interpersonal variables. The table is instructive as it shows the typical jobs associated with both sides of interpersonal tasks. The upper panel shows the top-bottom jobs list for ITI. The top-ITI list is exclusively occupied by jobs in health, education, social work and clergy, sales, and personal services.

The lower panel of the table shows top and bottom occupational rankings of within-firm interactions. While the top is dominated by management and supervisory jobs, the bottom is mostly characterized by manual task intensive jobs. Although there is some overlap between typical ITI and within-firm intensive occupations, the list suggests that they capture different aspects of interactions. For instance, the occupation

14 See data appendix for initial steps of task variable construction.

of barbers in the bottom within-firm interactions list suggests that this job requires very low levels of help of or coordination with others in the firm. Yet its ITI score is above average as it requires communication with customers.

Two additional insights are suggested by the comparison of upper and lower panels of Table 1.A.1. First, in terms of skills, ITI shows great diversity while within-firm interpersonal interactions seem to be positively sorted. High-skilled occupations such as therapists and pharmacists in contrast to bartenders and parking lot assistants appear as the typical high-ITI occupations, whereas computer programmers and lower skilled machine operators coexist among the lowest-ITI jobs. On the other hand, the divide between skills in highest and lowest within-firm interpersonal intensive occupations is clear. Secondly, ITI occupations tend to be correlated with all kinds of service-related jobs while there is no clear pattern for within-firm interactions with respect to services.

Differences in their distribution along skills and service activity are potentially two key distinctions between ITI and within-firm interactions. Another piece of evidence in the same direction is given by Figure 1.1 which shows smoothed task scores by mean occupational wages in 1980. This graphical tool is frequently employed in the literature on labor market polarization. Mean occupational wages can be seen as a proxy for market-relevant skills (e.g, Autor, Katz, and Kearney, 2008; Autor and Dorn, 2013; Goos and Manning, 2007). It is also known that both tails of the wage distribution host jobs that are intensive in service activity (Barány and Siegel, 2017). The figure indicates that ITI is equally high in the lowest and highest paid jobs while lowest scores are recorded for the middling jobs. On the other hand, within-firm interactions display a roughly monotonic increase along the wage structure.

Guided by the information on the typical interpersonal-service and within-firm interactive occupations, next I formally test how both measures differ in terms of reflecting service-activity and skills using direct measures in Table 1.2. The left hand side variables on the left and right panel of the table are occupational measures of skill and service sector specialization calculated from Census as the long-run (1980-2010) mean years of education and employment share of service sector for each occupation.

The left panel shows the partial correlates of two types of interpersonal interactions with skills. Columns (1) and (3) indicate that both measures are correlated with skills though the association is much smaller for ITI. Columns (2) and (4) include major occupation-group dummies in order to see the strength of relationship within certain occupation types. Under this specification within-firm interactions are still related to skills (column (4)) while ITI is not (column (2)).

The diverging roles with respect to service specialization is starker compared to skills as shown on the right panel. ITI is strongly related to service-activity (columns (5) and (6)). Within-firm interpersonal tasks are not associated with services in general (columns (7)). When the major occupation dummies are in the regression, shown in the last column, the coefficient of within-firm interactions changes sign to negative. The table suggests that ITI not only conceptually but also empirically stands out as a measure that captures the key character of service activity in the labor market without having a particular emphasis on skills.

ITI and Other Task Characteristics

The previous discussion limits the comparison of ITI according to the direction of interpersonal interactions. In this part, I extend the discussion to include other types of task characteristics. These include interpersonal variables from other occupational information sources and relevant alternative task variables in the literature.

Dictionary of Occupational Titles (DOT) is the predecessor of O*NET and still used as a reference for occupational task characteristics. It is also rich in terms of interpersonal task aspects. Using the interpersonal variables of DOT can provide additional insights on ITI. I show how selected DOT measures are related to ITI and within-firm interactions in Table 1.3 by partial correlations. The first observation is that the two measures are distinct in their association with DOT tasks reflecting intelligence, data and creative requirements. ITI seems unrelated to these set of characteristics, while within-firm interpersonal tasks are strongly correlated. The fourth row shows the partial correlation between direction, control, and planning variable of DOT, which is the original non-routine cognitive and interpersonal measure of Autor, Levy, and Murnane (2003). Insignificant and low correlation with ITI and significant and high correlation with the within-firm measure summarize the difference between two kind of interactions. The two types of interpersonal tasks also have similarities, which are mainly regarding common interpersonal communication that are measured by DOT variables of dealing with people, talking, and people complexity. The last row shows that the variable measuring the task intensity for influencing people is positively related to ITI and does not exhibit significant correlation with within-firm interactions. The main message of the table, which complements Table 1.2, is that ITI is unattached to task requirements that involve more cognitive and complex abstract skills in contrast to within-firm interpersonal tasks. On the other hand, both are significantly related to people tasks that are dominantly characterized by non-cognitive content, though ITI shows a stronger association.

The literature on task demand discusses the impacts of technology and trade at the task level, and some of them include elements of interpersonal interactions. First, routinization hypothesis asserts that the ICT revolution that took place in the last decades of 20th century replaced workers who are performing tasks that are intensive in routine content and at the same time low in abstract and manual content. The abstract content is composed of two non-routine cognitive task aspects: analytical and interpersonal. Therefore, it is important to establish whether ITI represents a distinct task aspect relative to cognitive interpersonal tasks. I already show in the discussion above that ITI is not closely connected to tasks requiring direction, control, and planning (DCP), which is used as the cognitive interpersonal measure in the routinization literature. Cognitive interpersonal tasks are particularly intense in managerial and organizational roles in the workplace, and hence are more related to within-firm interactions.

Second, I compare ITI with the offshoring measures in the literature. Offshoring hypothesis predicts that tasks, which do not require the material presence of the worker while performing the task, are subject to replacement by international trade in tasks (Blinder, 2009). Following this line of reasoning the literature developed measures of offshorability building on O*NET database (Autor and Dorn, 2013; Firpo, Fortin, and Lemieux, 2011; Jensen and Kletzer, 2010). The task characteristic subject to offshorability is conceptually not related to ITI. However the indicators of offshoring in the literature suggest a correlation with ITI score because some of the jobs requiring interactions with customers also necessitates the presence of worker. Nevertheless this overlap is only partial since there are occupations with high ITI and offshorable at the same time such as some clerical and sales occupations; and also occupations that cannot be offshored and low in ITI such as manual intensive repair jobs.[15]

15 Blinder (2009) compares a subjective measure of offshoring to an objective measure developed from the O*NET database. The 3 out of 5 O*NET attributes used in the objective measure are also included in ITI, making both measures potentially highly correlated. Blinder (2009) reports that their subjective measure has a low rank correlation ($\rho = 0.16$) with the objective one and that there are large discrepancies between the two. Blinder (2009) and Blinder and Krueger (2013) argue that subjective measures by ex-

The current literature often only discusses the conceptual differences between routinization and offshorability measures, as I did in the previous paragraphs for ITI. Conceptual differences are necessary to establish the essential independence of tasks, however the overlapping elements have the potential to dominate the distinctive characteristics in the constructed measures. Whether this is the case is hard to assess. The main difficulty arises since the constructed measures combine several occupational characteristics that share common elements across different measures. For instance, non-routine manual tasks decrease both offshorability and routinizability while routine cognitive tasks increase both. Furthermore, non-routine manual and routine cognitive tasks form quite distinct task aspects. Fortunately, this does not apply when it comes to comparing ITI to main drivers of task demand in the literature since the task variables that make ITI are conceptually quite close, i.e., they are all about customer related interactions. Therefore in the following I compare a task variable that sufficiently characterizes interpersonal-service tasks to several others which span the range of task routinizability and offshorability. Such comparison can be seen as a validity check for the claims suggested as conceptual differences.

The proxy used for ITI is the O*NET variable "dealing with external customers". In Figure 1.A.1 I plot the standardized task score of this variable against several individual variables of routinization and offhsorability for the 322 consistent occupations. ITI is positively related to the importance of repeating the same tasks, which captures the basic element of routine and offshorable work. It does not show a monotonic overall pattern with the non-routine manual task intensity variable, moving and handling objects, which makes the task less likely to be replaced by computers and workers in foreign countries. These two observations sharply contrast with the approach that places non-cognitive interpersonal tasks into non-routine manual (e.g., Goos, Manning, and Salomons, 2009), as customer interactions seem to be neither non-routine nor manual. ITI is positively related to communication technologies, proxied by the use of telephone and email while performing the task, and in this sense contains offshorable characteristics. In sum, interactions that target customers seem to be either increasing or unrelated with the key elements of routinizability and offshorability despite the negative correlations between constructed measures.

perts are better in determining the offhsorability of occupational tasks. Therefore it can be expected that better offshorability measures exhibit low correlation with ITI, supporting the importance of conceptual differences.

Finally, Table 1.A.2 provides an overall summary regarding the comparison of task measures by showing average task scores transformed into percentiles for each major occupation category. [16] Interpersonal-service task measure differs from the routinizability and offshoring mainly because it is jointly and similarly intensive in managerial/professional, clerical and sales, and personal service jobs. This signifies the key properties of ITI discussed above, that is, reflecting the service-task content with a weak association with worker skills.[17] In fact, routinizability and offshorability measures are distributed more similarly compared to ITI across major occupation groups. It is also evident from the table that the mean intensities of within-firm interactiveness and abstract tasks follow very similar distributional patterns.

1.4 ITI and the Shifting Task Demand

ITI, both conceptually and empirically, captures the key aspects of service production in the labor market. Therefore, considering the continuous rise of service employment it can be expected that employment is attracted to jobs with higher interpersonal-service content. In this section I document and characterize the shifting task demand into interpersonal-service intensive occupations. I first study the aggregate measures of task demand and also track the evolution of economy-wide task representation since the late 1960s. Then I evaluate the average impact of ITI in explaining relative employment demand growth across occupations in the long run. I keep the comparative approach of the previous section throughout the analysis.

The first evidence regarding shifting task demand towards interpersonal tasks is provided by Figure 1.2, showing the employment-weighted mean task scores in the US labor market from 1968 to 2014, where 1968 scores are normalized to 1. Task scores are time invariant percentiles of corresponding task variables for each occupation, hence the variation through time comes from the changing representation of occupations in the economy.[18] In the figure, the two popular explanations for task

16 Routinizability measure, referred to as RTI, is developed by Autor and Dorn (2013), which is the standardized score of the log of routine task divided by the multiplication of abstract and manual tasks intensity scores. Routine, abstract and manual task scores are developed as a combination of the original DOT variables following Autor, Levy, and Murnane (2003). Offshoring measure is developed by Autor and Dorn (2013) following the categorization of Firpo, Fortin, and Lemieux (2011).

17 In addition, Table 1.A.3 shows that routinizability and offshorability measures have no association with service sector specialization of occupations.

18 This approach follows Autor, Levy, and Murnane (2003) which is then used by others (e.g., Borghans, Ter Weel, and Weinberg, 2014; Deming, 2015).

demand changes in the US economy are compared to ITI. The evolution of ITI in the economy can be well approximated by a linear trend while routinizability and offshorability follows a non-monotonic course. The almost-monotonic rise of ITI's representation in the labor market is in line with the growth of services during the same period. Routinizable occupations, measured by RTI index, expand during 1970s, followed by a steady decline starting with 1980 until early 2000s when the trend is even reversed for a short time. Overall, the bulk of the impact of routinization seems to take place in a period when personal computers had been increasingly adopted in the workplace, consistent with routinization hypothesis. The economy-wide offshorability oscillates around its 1968 level until mid-1990s, which then displays a mild trend of decline. The decline accelerates further in early 2000s and then aggregate offshorability follows a flat path. This appears to be consistent with offshorability hypothesis which suggests that the task demand for offshorable jobs decline as a result of increasing globalization together with global adoption of ICT. As of 2014 the US labor market is considerably more interpersonal-service intensive, less routinizable to a lesser extent, and slightly less offshorable compared to the late 1960s.

An indirect insight from the figure is that the task variables are quite different with respect to how the task demand evolves over time. There are periods when the course of different tasks in the economy exhibit certain correlations and others when they correlate in the opposite direction. This observation supports the viewpoint of this paper on the distinctive labor market-relevant characteristics represented by ITI, as well as the essential difference between routinizability and offshorability emphasized in the previous literature (Autor and Dorn, 2013; Blinder and Krueger, 2013; Goos, Manning, and Salomons, 2014), despite correlations across occupation scores.

Figure 1.2 suggests ITI and RTI as the two important task aspect regarding the changing occupational structure in the economy. Therefore in the following, I dig deeper into the potential connection between ITI and RTI by performing the same analysis in Figure 1.2, this time comparing ITI and components of RTI index. Panel A of Figure 1.3 includes the computed series for abstract, routine, and manual tasks, which form the key task categories of routinizability. The figure captures the rise in non-routine abstract tasks, the decline of routine tasks and relatively stable movement of manual tasks as in Autor, Levy, and Murnane (2003). Decline of routine occupations start with 1980s, roughly matching the period when computerization intensifies. The figure also reveals the source of stagnating RTI starting with 2000s. Routine and abstract tasks both slow down compared to 1980-2000 period although the flat movement is more emphasized in abstract tasks.[19]

The figure also indicates that roughly between 1980 and 2000 both ITI and abstract tasks followed similar trajectories. Given the cognitive interpersonal element embedded in the abstract task measure (i.e., tasks summarized by direction, control and planning activities) this comovement can stem from correlations between the two measures. In order to address this concern I show the result of a counterfactual exercise at Panel B. The solid lines indicate the original task variables while dashed lines show the adjusted series. The grey dashed line, Abstract*, is the residuals from the regression of abstract measure on ITI. The other, ITI*, is the residuals from regressing ITI on the abstract measure. Therefore the former shows the abstract measure that is uncorrelated with ITI and the latter shows the alternative ITI measure that is orthogonal to the abstract attributes. Both are transformed into percentiles and subject to the same computation steps with the original series.

The adjustment yields lower growth in both tasks but in different ways. ITI and its adjusted version decouple starting with early 1980s. The gap widens throughout 1990s then remains roughly the same. This can be potentially explained considering the impact of ITI's positive correlation with the non-routine interpersonal tasks since routinization intensifies after the 1980s and reaches its peak during the 1990s. On the other hand, adjusted abstract task measure disengages from its original since the initial sample period while the difference only gets larger with time. The slowdown in abstract tasks is more emphasized in its adjusted version. More precisely, between 2000 and 2014 the abstract measure that is orthogonal to ITI grows at a rate of -0.01 percent per annum compared to average annual growth rate of 0.41 percent between 1980 and 2000. In contrast, adjusted ITI indicates a more pronounced rise by growing annually 0.30 percent after 2000, which is almost identical to the growth of the original ITI measure during the same period and quite close to the historical growth rate before 2000.

Though the visual evidence from Figure 1.2 is instructive, a more sophisticated understanding on the rising importance of non-cognitive interpersonal tasks in the labor market can be obtained by a regression model. Motivated by Figure 1.2 on the long-run stability of task shifts towards ITI, I use 1980-2010 changes in occupa-

19 In an attempt to update Autor, Levy, and Murnane (2003), Autor and Price (2013) documented the flat movement in abstract tasks for the first time.

tional employment demand indicators from Census and ACS and run the following regressions:

$$\Delta e_j = c + \sum_{x \in X} \beta_y^x x_j + u_j, \tag{1.1}$$

where Δe_j denotes the long-run log change of the employment demand variable (total hours or total wage income) e between 1980 and 2010 for occupation j; x is some variable computed at the task level such as ITI, belonging to a set of occupation-specific variables X; β_y^x corresponds to the impact of task x on employment demand growth; and c is the constant term.

Estimated OLS coefficients of equation (1.1) when dependent variable is the log change in total hours are reported in Table 1.4. I address different specifications under each column. Column (1) estimates a significant positive impact for ITI alone. Column (2) reports a significant negative coefficient for routinizability index. Under column (3) I include both variables. Interestingly, RTI becomes insignificant as ITI's coefficient does not shrink too much. Column (4) reports the specification where the three elements of routine task intensity are separately in the regression. Abstract and routine tasks are significantly associated with increasing and decreasing employment demand, respectively. The manual task intensity on the other hand, is not associated with demand growth. This is in line with the literature on routinization as well as the introductory analysis of this section. Similar to the joint routinization measure, having elements of routinization does not change the high and significant impact of ITI (column (5)). In column (6) the offshorability measure has an impact similar to RTI, which also vanishes with the presence of ITI (column (7)). Another alternative is SBTC at the occupation level. I use long-run mean years of schooling for an occupation as the skill variable. Column (8) confirms the skill-biased rise in employment demand at the level of detailed occupations. In column (9) when they are in the regression jointly with ITI, both variables remain with positive and significant impact. Column (10) reports the regression with all variables, which once again confirms that ITI is a strong predictor of employment growth.

In the last two columns of Table 1.4, I include dummies for six major occupation groups that are listed in Table 1.A.2. Using major occupation group dummies can also be seen as way to jointly account for many factors that lead to job polarization (e.g., routinization, offshoring, decline of manufacturing, de-unionization) since the literature typically observes a rise in employment share and wages in managerial, professional and technical jobs as well as service occupations; and a decline in relative demand for production, sales, operators, transportation, and construction jobs. In column (11) the coefficient of ITI shrinks by a considerable amount while still being a significant predictor. In column (12) all other alternative task variables are included in addition to ITI. ITI's estimated coefficient is the highest and the only significant estimate. Taking the lower bound of ITI estimates, one standard deviation higher ITI leads to 0.5 percentage points faster annual growth in occupation employment.

Table 1.5 shows identical specifications to the previous table when dependent variable is 1980-2010 change in log wage bill. It also includes information on the relative price of the occupational labor input. Compared to Table 1.4 higher coefficients are estimated for ITI. On the other hand within-occupation group associations of ITI to employment and wage bill growth are similar.

The importance of the simple analysis here is that it provides a horse race of tasks in occupation growth using data that are consistently available in the long run at the most detailed level of occupations. Tables 1.4 and 1.5 establish that ITI is the dominant long-run driver of relative employment demand growth.[20] In the next section, I complement the study of ITI's role in the economy by exploring its linkages with productivity and technology.

1.5 ITI and Technology

From simple correlations to occupational distributions, or through inspecting the relationship with occupational demand, the evidence suggests that ITI stands out as an important task aspect. However, nothing is yet known about how it relates to technology. Nevertheless, considering the close connection of ITI to service production, insights from the literature on the service economy suggests a certain direction on ITI-technology relationship.

20 These tables aim to show the growing importance of interpersonal-service tasks in the labor market through comparisons with popular task measures used in the literature. Table 1.A.4 provides evidence that ITI performs also superior also compared to within-firm interactions, which are closely correlated with social and cognitive skills. A key observation from that table is that controlling for the skill intensity of occupations leaves no predictive value for within-firm interactive task content, in contrast to interpersonal-service content.

Low productivity growth in services has been known by economists for a long time. It is also a widely believed channel of structural change, which often finds its representation in the structural change models as a slower sector-specific technology growth in services. Even starting with early works of William Baumol and Victor Fuchs, the central argument on why services have lower productivity growth is concentrated on the customer-producer interactions that are complex, fragile and hard to change in terms of the style of production. This aspect of interpersonal interactions is precisely what ITI measures. Therefore a task-based explanation for slower sector-specific technology growth rate in services suggests slower occupation-specific technology growth correlated with ITI.

The recent literature on tasks and technology is dominated by routinization hypothesis. Similar to the role of sector-specific productivity growth in the structural change models, in the literature the success of RTI in explaining employment reallocation (in the reverse direction) stems from the fact that RTI-intensive occupations have a faster productivity growth as a result of more intensive computerization. Since both ITI and RTI are important task aspects in terms of the reallocation of employment, the comparison between the two with respect to technology is the main discussion in this section. Recently, both technological growth that is slower in service activities (Barány and Siegel, 2017; Duernecker and Herrendorf, 2017) and faster in routinizable ones (Autor and Dorn, 2013; Goos, Manning, and Salomons, 2014) are studied, but characterization on how the two connect to the technological change at the task level remains obscure. Below I first show that the stylized view on productivity and tasks hold at industry level.[21] Then I provide novel evidence on how interpersonal-service content relates to developments in ICT technologies, which are well known to be the basis of recent routinization experience.

If customers really act as a brake on productivity, we should observe slower labor productivity growth not only in the broad service sector but also in detailed sectors that more intensively employ interpersonal-service tasks. While the well known examples of industries with slowest labor productivity growth or with highest relative price increases such as health and education services can be easily recognized as high-ITI industries, it is of interest of this section whether this association holds throughout the economy. In addition, if routinization enables more exposure to labor-

21 Unfortunately, to the best of my knowledge there exist no data that measure productivity across years at the occupation level.

saving technologies, labor productivity should grow faster in industries with higher RTI. I formally test these claims using labor productivity data from BLS between years 1987-2014 below. The productivity data is detailed at finer industry categories however they cannot be reliably matched to industry codes in CPS or Census where I compute employment-weighted industry-task intensities. Instead, I generate industry task intensities for 12 broad NAICS categories. In particular, I estimate the following equation:

$$a_{it} = \sum_{x \in X} \beta_{xm} \left(x_m \times time \right) + d_t + \eta_i + u_{it} \qquad (1.2)$$

where a_{it} is the log of labor productivity index for detailed industry i at time t; x_m is the time invariant measure of broader sector task intensity[22] of task x performed by the workers in broader sector m in a set of tasks denoted by X; $time$ is a running variable for year; d_t are year dummies; η_i are industry dummies. β_{xm} captures the impact of industry task intensity on the growth rate of productivity in broader NAICS sector m.

Table 1.6 column (1) reports β_{ITI} and its standard error. As expected, the coefficient of ITI is significantly negative and statistically significant. Sectors with higher ITI exhibits slower labor productivity growth. Column (2) reports positive and significant coefficient for β_{RTI}. The last column includes both RTI and ITI in the regressions, where reported coefficients shrink only little compared to individual estimates under other columns. Industry labor productivity trends are in line with the predictions of the stylized view.

In the remaining I explore the potential channel of technology through which ITI operates. Given that routinization is driven by widespread use of ICT technologies, there are two potential cases that can explain the trends in employment and productivity. In the first case, although ITI and RTI are distinct tasks, they are complementary measures of routinization. The implication under this scenario is that the framework of Autor, Levy, and Murnane (2003) should be improved by considering interpersonal-service tasks. This result is similar to how Goos, Manning, and Salomons (2009) approach routinization. The second possible case is that interpersonal-task intensity is not related to routinization process, and hence it should be evaluated as a separate

22 I simply use standardized long-run mean task scores for each sector using CPS labor supply weights. Task score rankings across sectors are remarkably stable over time, the evidence for which is available upon request.

channel. The second case is closer to how the structural change literature tends to view the service activity.

The literature suggests a specific channel regarding how RTI leads to faster labor productivity growth. The mechanism of routine-biased technical change assigns a key role to capital, specifically to ICT capital. High RTI occupations, industries, and economies go through greater levels of ICT intensification, or computerization (Autor and Dorn, 2013; Autor, Levy, and Murnane, 2003). Given the negative association between routine tasks and ITI it is a valid concern whether slower productivity growth associated with ITI also stems from lack of automation. Therefore in the last part of this section I discover how ITI is related to recent technological advances in computing technology. I do it by providing evidence at the level of occupations, industries and local labor markets.

The first evidence comes from the O*NET database. I combine two occupational task variables on computerization and automation. The first one provides occupational information on the importance of interactions with computers. This variable reflects computerization but since it measures interactions with computers it might fail to capture computerization that took place without interactions. Therefore I use another variable, degree of automation, which indicates how automated the job is. Using only the latter variable might lead to overrepresentation of automation history beyond the recent technologies. Therefore, the combined measure is an average of two aspects of technology.

Table 1.7 reports the OLS estimation results from regression of the computerization measure on ITI, RTI and components of routinization framework.[23] The specification at Column (1) includes only ITI. The insignificant coefficient suggests that ITI is not a good predictor of computerization at occupation level. This reflects the fact that interactions with customers may or may not be subject to computerization depending on the other task characteristics of the job. One can find examples where ITI is related to lack of routinization (e.g., barbers) as well as cases with successful computerization (e.g., sales workers).

In contrast, column (2) shows that RTI is significantly related to computerization as expected by routinization hypothesis. Column (3) where both variables are in the

23 In particular, I estimate equations of the following kind: $C_j = \beta_0 + \sum_{x \in X} \beta_x x_j$, where C_j is the computerization measure for occupation j, x is a task measure in the task set X, and x_j is the corresponding task score.

specification reports similar point estimates for RTI while ITI's coefficient remains small and insignificant.

Remaining specifications go one step further from using the composite routineness measure and include the elements of routinization framework in the specifications. Column (4) reports the three task variables of DOT from Dorn (2009). As predicted by the routinization framework of Autor, Levy, and Murnane (2003), abstract and routine task intensive occupations experience greater computerization as cognitive complex tasks are complemented and routine tasks are substituted by computers. On the other hand, manual task intensity decreases computerization quite strongly, as computers are not capable of replacing non-routine physical tasks nor directly helping them. Column (5) reports that controlling for the components of the routinizability measure do not impact the ITI's (lack of) connection to computerization.

The last two columns give further insight by providing the most detailed breakdown of RTI. I use Acemoglu and Autor (2011)'s measures from O*NET. Column (6) suggests a nuanced understanding for the impact of non-routine cognitive tasks, which are mentioned as abstract in the previous paragraph. The source of complementarity in abstract content seems to be coming from analytic tasks, while cognitive interpersonal tasks which emphasize the managerial content has a negative effect on computerization. Cognitive and routine tasks lead to computerization while routine manual ones do not appear to be related to it. Finally, the non-routine cognitive task content from O*NET has a coefficient quite similar to manual task intensity variable of DOT. Column (7) indicates that ITI at the occupation level seems unrelated to the computerization measure in the face of the most detailed elements of the routinization framework.

Table 1.7 uses measures for ITI, RTI, and components of routinization that are constructed from detailed task variables, and the data are aggregated to 322 consistent occupations. In order to see whether results of Table 1.7 hold for more detailed occupation categories and more direct task variables Figure 1.A.2 plots the O*NET task variables "importance of repeating the same tasks" and "dealing with external customers" with the same computerization variable using 942 O*NET SOC occupation units. Obviously, the former is a rough measure for routineness and the latter is a good proxy for ITI. Occupations that are characterized by repeating the same tasks are the ones with greater levels of ICT intensity. Confirming the results from Table 1.7, occupations which require dealing with customers are not negatively related to ICT intensity. Instead, there is a slight positive association. The existing evidence from the detailed task database is far from suggesting a role for interpersonal-service tasks within the existing routinization framework.

Second piece of evidence is at industry level. BEA Capital Flow Table, 1997, provides a basic source for studying new purchases of ICT capital. It reports the purchases of new capital for 123 detailed industries. From the full set of detailed industries I redefine 66 that are compatible with CPS industry codes. ICT purchases are calculated as the sum of computers and peripheral equipment, office and accounting equipment, software and communication equipment. ICT share in new capital purchases is calculated as ICT purchases divided by total equipment purchases. I simply run regressions of the ICT intensification ratio on long-run employment weighted task intensities in Table 1.8.[24] Column (1) indicates a positive, small coefficient of ITI with a relatively large standard error. The unconditional association of ITI with ICT's share in new purchases does not provide any useful correlation as R^2 reported for column (1) is zero. This should be compared with the impact estimated for RTI since routinization hypothesis suggests a strong positive connection between RTI of an industry and intensification of ICT technologies. The large and significant coefficient of RTI in column (2) indicates that ITI is not very much related to ICT intensification of industries. This result does not change when ITI and RTI are jointly present, which is reported in the last column.

Last evidence on computerization and tasks comes from the US local labor markets in Table 1.9. I run regressions of adjusted PCs per employee in the local labor market on labor market-wide initial task intensities. The analysis here is similar to Autor and Dorn (2013)'s column (3) of Table 3. They show that routine specialization of an initial zone can predict the computer adoption in the following 10 years quite well. Here my aim is to see how ITI is compared to RTI, when the dependent variable is the computer intensity instead of adoption. I use Doms and Levis's adjusted personal computers per person measure calculated for 675 Commuting Zones (CZ) of the US for years 1990 and 2002 from Autor and Dorn (2013). This data counterpart of ICT intensity is relevant but incomplete since personal computers account for only a portion of ICT

24 Equations estimated are of the following form: $ICT_i = \beta_0 + \sum_{x \in X} \beta_x x_i$, where ICT_i is the ICT intensification measure for industry i, and x_i is the industry mean score of task x.

capital. Commuting Zones provide a natural geographic unit in terms of economic connections at the local level. In particular I estimate the following equation:

$$PC_{kst} = \delta_s + d_t + \sum_{x \in X} \beta_x x_{kst_0} + \epsilon_{kst}, \tag{1.3}$$

where PC_{kst} is the adjusted PCs per employee at commuting zone k, state s and time t for 1990 and 2000; δ_s are state fixed effects; d_t are time fixed effects; x_{kst_0} is the commuting zone task intensity for task x at initial time period, i.e. 1980.[25]

In Table 1.9 column (1) suggests that ITI is positively related to computer adoption. However, the effect becomes small and insignificant when controlled by the initial skill intensity of local labor markets, defined by the percentile ranking of commuting zone college worker share in employment, as shown in column (2). Columns (3) and (4) show that RTI leads to higher computer intensity even when conditioned on the skill intensity. The last column confirms that having ITI in the regression changes nothing regarding the RTI's coefficient and the fit of the model.

The evidence on ITI and ICT intensity is remarkably consistent at occupation, industry and local labor market level. It also suggests that ITI and RTI are not only distinct task characteristics, but they also reshape the structure of employment through different channels. While computerization enables faster productivity growth in high RTI tasks, high ITI tasks are relatively stagnant due to a reason apart from non-neutral progress in ICT. ITI slows down the productivity growth most likely in the form of a friction on the growth of neutral technology, which is effective regardless of worker skills and intensity of better capital. In the next section, I conceptually introduce this as task-specific technical change and develop a model which is consistent with the empirical observations documented in this paper.

1.6 Analytical Framework

In this section I study a general equilibrium model that can rationalize the empirical findings of the paper. First, I describe layers of production in the model where I introduce firms' problem in industry, task, investment and task capital production. Then

25 Commuting zone task intensity variables are first calculated following Autor and Dorn (2013) as the commuting zone share of employment that works in ITI or RTI intensive occupations. An occupation is ITI or RTI intensive if the occupation's corresponding task score lies within the highest tercile. I use the percentile transformed versions of the task intensities to allow comparison between ITI and RTI.

I include the household's consumption decision and analyze general equilibrium implications of the model regarding industrial and occupational reallocation of labor subject to exogenous changes in technology.

The task-based approach of the model suggests that technological innovations are occupation-specific. The model is similar to Goos, Manning, and Salomons (2014) and Duernecker and Herrendorf (2017) in having the industry-occupation structure. The model here is different from the former since I model routinizability of an occupation as an outcome of computing capital intensity and additionally study occupation-specific technical change in a general equilibrium setting.[26] It differs from the latter by allowing for routinization, and studying many sectors and occupations. The approach here can be seen as an extension of technology-driven structural change models (Acemoglu and Guerrieri, 2008; Ngai and Pissarides, 2007). Two forces of labor reallocation is occupation-specific technical change and capital deepening. The first channel can be seen as the occupation analog of Ngai and Pissarides (2007)'s industry-specific productivity growth. Though the idea employed is similar, the second channel is slightly different than what Acemoglu and Guerrieri (2008) suggest. They have homogenous capital and different capital shares in sectors leading to structural change while here I emphasize different ICT-capital shares within occupations while the share of task-capital aggregate (combination of ICT and other capital) is constant among occupations.

1.6.1 Industry Production

Perfectly competitive firms carry out industry production by combining task inputs produced for that industry. The output of each industry is then consumed by the household. The total number of industries is I and total number of occupations is J. The production follows the following CES functional form:

$$Y_{it} = \left[\sum_{j}^{J} (\phi_{ij})^{\frac{1}{\theta}} (T_{ijt})^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}, \tag{1.4}$$

where $i = 1, \dots, I$; $j = 1, \dots, J$; Y_i is output in industry i; T_{ij} is industry i's task input from occupation j; ϕij is exogenous task weight; and $\theta > 0$ is the elasticity of

26 Goos, Manning, and Salomons (2014) do not study the general equilibrium model, but take into account demand effects in their empirical analysis.

substitution between task inputs, which is assumed to be the same across industries. Firms take industry output price, p_i, and task price, τ_j as given and maximize profits at time t:

$$\max_{T_{ijt}} \left[p_{it} Y_{it} - \sum_{j}^{J} \tau_{jt} T_{ijt} \right]. \tag{1.5}$$

First order conditions imply that the optimal task input demand increases with higher output demand, output price, and lower task price:

$$T_{ijt} = \phi_{ijt} \left(\frac{p_{it}}{\tau_{jt}} \right)^{\theta} Y_{it}. \tag{1.6}$$

1.6.2 Task Production

At each industry there is a set of occupations that produce tasks by combining labor and task capital in the form of computing and non-computing capital.[27] I assume perfect competition within each occupation-industry pair and technology is only occupation-specific. Task producers hire labor and task capital to produce tasks to be used in industrial production:

$$T_{ijt} = A_{jt} L_{ijt}^{\alpha} E_{ijt}^{1-\alpha}, \tag{1.7}$$

where A_j is occupation-specific technology term; L_{ijt} and E_{ijt} denote labor and task capital respectively for occupation j operating under industry i. There are two types of task capital required for production. In particular I further assume that task capital is a Cobb-Douglas aggregator of computing capital, K_{ijt}^C, and other capital, K_{ijt}^N:

$$E_{ijt} = \left(K_{ijt}^C \right)^{\kappa_j} \left(K_{ijt}^N \right)^{1-\kappa_j}, \tag{1.8}$$

where κ_j is the occupation-specific share of computers in task capital.

Profit maximization problem of the task producer is as follows:

$$\max_{L_{ijt}, K_{ijt}^C, K_{ijt}^N} \left[\tau_{jt} T_{ijt} - w_{jt} L_{ijt} - p_t^C K_{ijt}^C - p_t^N K_{ijt}^N \right], \tag{1.9}$$

27 By computing capital, computers, or ICT capital I refer to all equipment that has been the subject of ICT revolution. The remaining task capital includes all other equipment and/or structures required to perform the task.

where w_j, p^C, p^N respectively denote wage rate, price of computing and other capital.

Occupation-specific technical change in the model is captured by the differential growth rates of A_j across occupations and the degree of routinizability is determined by a higher share of computer capital, κ_j. In order to see key mechanism of routinization one can construct the ideal price index for aggregate task capital E_{ij}:

$$p^E_{jt} = \left(\frac{p^C_t}{p^N_t}\right)^{\kappa_j} p^N_t \Omega_j, \tag{1.10}$$

where $\Omega_j = \kappa_j^{-\kappa_j}(1-\kappa_j)^{-(1-\kappa_j)}$. Equation (1.10) implies that across occupations relative price of task capital depends on κ_j only. The price of task capital aggregate, p^E_j, is also specific to occupation because of the share of computing capital. Therefore occupations effectively differ in terms of the cost of task capital they are subject to.

Consider a simple comparative statics exercise where the relative price of computing capital falls. The decline in the price of computers is the same for every occupation, but the cost of total capital decreases more in occupations with a higher share of computers. This leads to increasing use of computers relative to other capital. Therefore, a higher κ_j corresponds to a greater degree of computerization in an occupation while computers are becoming cheaper. Moreover, under Cobb-Douglas task capital aggregator, profit maximizing implies that the share of computers in total capital purchases should always be larger in occupations with higher κ_j:

$$\frac{p^C_t K^C_{ijt}}{p^E_{jt} E_{ijt}} = \kappa_j. \tag{1.11}$$

The demand for labor and the composit capital input is given by first order conditions of (1.9):

$$L_{ijt} = \frac{\alpha \tau_j T_{ijt}}{w_t} \tag{1.12}$$

$$E_{ijt} = \frac{(1-\alpha)\tau_{jt} T_{ijt}}{p^E_{jt}}, \tag{1.13}$$

where p^E_{jt} is defined as in equation (1.10).

1.6.3 Investment and Task Capital

In this section, I study the investment sector and production of the task capital. I start with a clarification on the the use of the term capital in the model. There are two types of *capital*. First is the household capital which is allocated to either investment sector or rented to be used in goods production. Second is the task capital that is obtained by transformation of household capital and then used as an input of task production. In this sense, task capital is measured in efficiency units of household capital. To avoid confusion, note that all K with an upper script letter corresponds to task capital as in the previous subsection, and K with lower script letter corresponds to household capital.

Investment Sector

There is a simple investment sector with AK production function. The investment good is given by $Y_{Xt} = B_X K_{Xt}$, where K_{Xt} is the household capital allocated to investment sector and B_X is the level of investment technology. The price of capital is r_t, hence the competitive structure of the sector ensures zero profits, i.e. $r_t = r = B_X$.[28] In addition, capital accumulates according to the following:

$$K_{t+1} = (1-\delta)K_t + Y_{Xt}, \tag{1.14}$$

where K represents total capital stock in the economy.

Production of Task Capital

All task capital is produced in another sector which is simply characterized by two types of firms transforming household's capital into computing or other task capital. I assume there is a continuum of perfectly competitive firms in each task capital subsector which use different technologies. Therefore, firms take prices p_t^C and p_t^N. The production function is given by $K_t^m = B_t^m K_{mt}$ for $m = \{C, N\}$, where B^m is the level of technology to produce capital type m. Recall that K with a lower script represents

28 Price of the investment good is normalized to one.

the quantity of household capital devoted to a particular type of task capital rented at price r. Capital prices and task capital technologies are connected by the following:

$$r = p_t^C B_t^C = p_t^N B_t^N \tag{1.15}$$

Equation (1.15) implies that the result of faster developments in the ICT technologies relative to technology of other capital is a greater decline in the relative price of computer.

There are two important things to note regarding the nature of capital-embodied technical change in this model. First, any fall in the price of capital does not necessarily mean computerization. What happens to relative price of computing is the key. Second, within each industry capital-embodied technical change may or may not be labor substituting, depending on industry-task demand. This point is further clarified in the last part of this section.

1.6.4 The Household

The representative household in this economy consumes the final output produced by industries, C_i for $i = 1, \ldots, I$, and has the following life-time utility:

$$\sum_{t=0}^{\infty} \beta^t \log C_t, \tag{1.16}$$

where $C_t = \left(\sum_i^I (\lambda_i C_{it})^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{\epsilon}{\epsilon-1}}$ is the CES consumption aggregator. $\epsilon > 0$ is the elasticity of substitution between goods, and λ_i is a preference weight of the consumer to good i. Consumers maximize utility by choosing the optimal saving and consumption subject to the following budget constraint:

$$\sum_i^I p_{it} C_{it} + K_{t+1} = (1 - \delta + r_t) K_t + w_t L_t. \tag{1.17}$$

The left hand side of the budget constraint is the total consumption in the current period plus household capital allocated for the next period. The right hand side involves the capital and wage income of the household plus the undepreciated household capital. The optimal allocation of consumption across goods and optimal allocation of total consumption across periods can be analyzed separately. First order conditions imply the following consumer demand for industry output:

$$C_{it} = \lambda_i^{\epsilon-1} \left(\frac{p_{it}}{P_t} \right)^{-\epsilon} C_t, \tag{1.18}$$

where the price index, P, is given by

$$P_t = \left[\sum_i^I \left(\frac{p_{it}}{\lambda_i} \right)^{1-\epsilon} \right]^{\frac{1}{1-\epsilon}}. \tag{1.19}$$

The inter-temporal consumption decision is governed by the following:

$$\frac{P_{t+1} C_{t+1}}{P_t C_t} = \beta \left(1 - \delta + r_t \right). \tag{1.20}$$

1.6.5 Equilibrium

At each time $t \geqslant 1$, given occupation-specific technology for each occupation $\left\{ A_{jt} \right\}_{j=1}^J$, technology for computing and other capital B_t^C and B_t^N, time invariant investment technology B_X, total hours of household L_t, and the initial household capital stock K_0, equilibrium in this economy is defined by industry output prices $\{p_{it}\}_{i=1}^I$, task prices $\left\{ \tau_{jt} \right\}_{j=1}^J$, price of computing capital p_t^C, price of other capital p_t^N, wage rate w_t, rental price of capital r_t; consumption bundle $\{C_{it}\}_{i=1}^I$, industry output $\{Y_{it}\}_{i=1}^I$, task output $\left\{ \left\{ T_{ijt} \right\}_{j=1}^J \right\}_{i=1}^I$, labor hours, computing and other capital, and investment capital $\left\{ \left\{ L_{ijt}, K_{ijt}^C, K_{ijt}^N, K_{Xt} \right\}_{j=1}^J \right\}_{i=1}^I$ such that:

1. Households choosing C_{it} and K_{t+1} maximize utility in (1.16) subject to (1.17),
2. In each industry, firms maximize profits according to (1.5),
3. In each occupation of each industry, firms maximize profits according to (1.9),
4. As a result of competition and profit maximization (1.15) holds in the task-capital market, and $r_t = B_X$ holds in the investment sector,
5. Household capital accumulates subject to (1.14),
6. Markets clear:
    a) $C_{it} = Y_{it}$ for $i = 1, \ldots, I$,

b) $Y_{Xt} = B_X K_{Xt}$

c) $L_t = \sum_{i=1}^{I} \sum_{j=1}^{J} L_{ijt}$,

d) $K_t = K_{Xt} + K_{Ct} + K_{Nt} = K_{Xt} + \frac{K_t^C}{B_t^C} + \frac{K_t^N}{B_t^N} = K_{Xt} + \sum_{i=1}^{I} \sum_{j=1}^{J} \left(\frac{K_{ijt}^C}{B_t^C} + \frac{K_{ijt}^N}{B_t^N} \right)$.

It can be shown that the economy is subject to a generalized balanced growth path where aggregate output, aggregate capital, total consumption expenditure, and wages grow at rate $\beta \left(1 - \delta + B_X\right)$. The key in the reallocation of labor is industry output and task prices which are given by the following equations:

$$p_{it} = \left(\sum_{j}^{J} \phi_{ij} \left(\tau_{jt}\right)^{1-\theta} \right)^{\frac{1}{1-\theta}}, \tag{1.21}$$

$$\tau_{jt} = \frac{1}{A_{jt}} \left(\frac{w_t}{\alpha}\right)^{\alpha} \left(\frac{p_{ijt}^E}{1-\alpha} \right)^{1-\alpha}. \tag{1.22}$$

1.6.6 Technical Change, and Predictions of the Model

In this part I study the model predictions that can explain the empirical observations of previous sections. I proceed by linking technology to tasks based on two independent assumptions. First, I assume that ITI of an occupation is inversely proportional to the growth rate of occupation-specific technology parameter A_{jt}. This reflects the idea that interactions with customers slow down technological progress realized in an occupation for reasons other than improvements in task capital, such as customer acceptance and incapabilities. Second, I assume that the time invariant share of ICT (or computing) capital in task production κ_j is proportional to RTI of an occupation. Although in fact this share may change with respect to time and technical developments, I follow the literature on assuming a fixed level of routinizability at the task level. The rest of the assumptions characterize the well-known fall in the relative price of ICT capital. That is straightforward to achieve in the model by assuming an increasing time-path for B_t^C / B_t^N, i.e., higher relative growth rate in computer technology.

The following two results characterize the model's task-driven forces of employment reallocation. Note that all claims are stated under the characterization of technology above.

RESULT 1 (OCCUPATIONAL REALLOCATION OF LABOR): *Suppose that $\theta < 1$. Employment and wage bill growth is higher in more interpersonal-service intensive and less routinizable occupations.*

I simply illustrate this result by comparing two different occupations, j and j', within industry i. Using equations (1.6), (1.12), and (1.22) the relative demand for labor is given by

$$\frac{L_{ijt}}{L_{ij't}} = \left(\frac{\Omega_j}{\Omega_{j'}}\right)^{(1-\alpha)(1-\theta)} \left(\frac{\phi_{ij}}{\phi_{ij'}}\right) \left(\frac{A_{j't}}{A_{jt}}\right)^{1-\theta} \left(\frac{p_t^C}{p_t^N}\right)^{(1-\alpha)(1-\theta)(\kappa_j-\kappa_{j'})},$$

where Ω_j is defined as in equation (1.10). Inspection of the equation above reveals that when $\theta < 1$ the occupation-specific technology is inversely related to relative employment levels between two occupations. Therefore, occupation that has a slower growth in A_{jt}, i.e., occupation with higher ITI, attracts more employment. In addition, given the declining relative price of ICT capital and $\theta < 1$ the last fraction on the right-hand side is decreasing when $\kappa_j > \kappa_j'$, i.e, higher RTI leads to lower employment growth and declining share in employment. Since the same holds in every industry the result generalizes to the overall employment share of occupations. Since wages across occupations equalize in this model the result for wage bill follows.

RESULT 2 (REALLOCATION OF LABOR ACROSS INDUSTRIES): *Suppose that $\epsilon < 1$. Industry employment growth is increasing (decreasing) in greater specialization in occupations of higher ITI (RTI).*

This result can be simply illustrated by comparing the labor in two arbitrary industries. Zero profit in industry production, and equations (1.12) and (1.18) imply that employment in industry i relative to industry i' is

$$\frac{L_{it}}{L_{i't}} = \left(\frac{\gamma_i}{\gamma_{i'}}\right)^{-(1-\epsilon)} \left(\frac{p_{it}}{p_{i't}}\right)^{1-\epsilon},$$

where $L_i = \sum_{j=1}^{J} L_{ij}$ is total employment in industry i. Last term on the right-hand side is the relative industry price. Inspection of (1.21) reveals that industry price is increasing in the task prices proportional to their production weights ϕ_{ij}. From (1.22) task prices are increasing in ITI and decreasing in RTI. Relative price of industries with higher ϕ_{ij} in growing occupations consequently increase more, which turns into a relative rise in employment if $\epsilon < 1$.

Both results above are directly related to proposition 2 of Ngai and Pissarides (2007). When task intensities and industries are poor substitutes in production and consumption, respectively, employment is reallocated into occupations and industries exhibiting slower productivity growth. Next result explicitly connects task intensities to labor productivity growth.

RESULT 3 (LABOR PRODUCTIVITY GROWTH): *Occupation and sector labor productivity growth is decreasing in ITI and increasing in RTI.*

An occupation's log of labor productivity is given by the following:

$$\log\left(\frac{T_{ijt}}{L_{ijt}}\right) = (1-\alpha)\log\left(\frac{1-\alpha}{\alpha}\right) + (1-\alpha)\log w_t + \log A_{jt} - (1-\alpha)\log p^E_{ijt}.$$

It is clear that occupations with higher growth in occupation-specific technology (i.e. lower ITI) and lower growth in task-capital prices (i.e. higher RTI) are subject to faster growth in occupational labor productivity. Similarly, the model implies the following sectoral labor productivity equation:

$$\log\left(\frac{Y_{it}}{L_{it}}\right) = \log\left(\frac{w_t}{\alpha}\right) - \log p_{it}.$$

As argued in Result 2, inspection of (1.21) and (1.22) suggests that costs grow slower in sectors with lower ITI and higher RTI intensity. Since ITI and RTI are occupation-specific this implies that sectors that are specialized towards occupations with low ITI and high RTI exhibit faster productivity growth. In fact, labor productivity regressions of Table 1.6 can be obtained from the above equation when $\theta = 1$.[29]

Results studied so far do not require the model's specific assumptions linking ITI and RTI to different sources of technical change. It does not matter for results 1-3 whether both tasks are modeled as affecting occupation-specific technical change or ICT capital share. The next one shows where the distinct roles assigned to both tasks matter.

29 In this case, the right hand side of log labor productivity equation becomes $(1-\alpha)\log\left(\frac{1-\alpha}{\alpha}\right) + (1-\alpha)\log w_t + \sum_{j=1}^{J} s_{j|i}\log A_{jt} - \sum_{j=1}^{J}(1-\alpha)\, s_{j|i}\log p^E_{ijt}$, where $s_{j|i}$ is the constant share of task j in sector i's production such that $\sum_{j=1}^{J} s_{j|i} = 1$. This form enables linear estimation of labor productivity on industry employment-weighted means of occupation-specific characteristics.

RESULT 4 (ICT INTENSIFICATION): *ICT intensification is only related to RTI. In particular, share of ICT capital to other capital, the share of ICT in new purchases of capital, and ICT-capital per employment in the economy depends on RTI and not on ITI.*

This result is intuitive since the only difference with respect to capital across occupations is κ_j in the model which is assumed to be proportional to RTI. In the remaining discussion I show that for different measures of ICT intensification the estimated linear equations in the paper follow directly from the model when $\theta = 1$, i.e., sector production function is in Cobb-Douglas form.[30]

The most direct ICT intensity measure that can be derived from the model is the ratio of ICT capital to the other task capital:

$$\frac{K_{jt}^{C}}{K_{jt}^{N}} = \left(\frac{p_t^N}{p_t^C}\right)\left(\frac{\kappa_j}{1-\kappa_j}\right),$$

which is straightforward from (1.10) and (1.11). It is clear from this representation that ICT capital has a greater share for occupations with greater RTI, and regardless of the relative price of computers, the ranking of occupations in terms of ICT capital's share is constant. Consequently, the change in the computer capital intensity, which can be seen as a measure of computerization, is proportional to RTI. Taking the occupation level measure that combines the importance of interacting with computers and the degree of automation as a proxy for ICT intensity (or intensification following the reasoning in Autor, Levy, and Murnane (2003)), its strong and significant association with RTI (and not with ITI) in Table 1.7 is predicted by the model.

The second ICT intensification measure is the change in ICT capital value relative to total task-capital change in an occupation or industry. For occupation j this ratio is given simply by κ_j:

$$\frac{p_{t+1}^{c} K_{ijt+1}^{c} - p_t^{c} K_{ijt}^{c}}{p_{t+1}^{E} K_{ijt+1}^{E} - p_t^{E} K_{ijt}^{E}} = \kappa_j.$$

One can compute this measure at sector level rather than occupation, it becomes the following:

$$\frac{\sum_{j=1}^{J} p_{t+1}^{c} K_{ijt+1}^{c} - \sum_{j=1}^{J} p_t^{c} K_{ijt}^{c}}{\sum_{j=1}^{J} p_{t+1}^{E} K_{ijt+1}^{E} - \sum_{j=1}^{J} p_t^{E} K_{ijt}^{E}} = \sum_{j=1}^{J} s_{j|i}\kappa_j.$$

30 In this case the sector production function becomes $Y_{it} = \prod_{j=1}^{J} T_{ijt}^{s_{j|i}}$, where $s_{j|i}$ is defined as in footnote 29.

Therefore the ICT intensification in a sector's total purchases of capital should be predicted by its RTI score as a weighted average across occupations employed in that sector. This sheds light on the results of Table 1.8, where $s_{j|i}$ is approximated by occupation j's share in industry i employment over the long-run.

Lastly, I study the model's implication on ICT capital per employment in the whole economy. Let's assume that there is a set of closed economies indexed with e. For an economy e the ratio is calculated as:

$$\frac{K_{et}^{C}}{L_{et}} = \frac{w_{et}}{p_t^C}\frac{1-\alpha}{\alpha}\sum_{i=1}^{I}\sum_{j=1}^{J}\frac{L_{eijt}}{L_{et}}\kappa_j,$$

where L_{et} is the total labor supply in the economy.

The equation above suggests that ICT capital per labor employed in the economy depends on wages, ICT capital price and an economy-wide average of ICT's share in task-capital, κ_j. It is clear that the economy's aggregate level of routinizability predicts its ICT intensity, and that ITI plays no role in it. Assuming that ICT price is similar across economies, the equation also suggests that economies with higher wages should also have higher adoption of ICT capital (as well as other capital since labor's marginal productivity is higher). Considering each local labor market as a distinct economy, this equation justifies the regressions of computer adoption in Table 1.9. Furthermore, it provides an explanation for why skill intensity of commuting zones successfully predicts computer adoption too.

1.7 Conclusion

In this paper I document that from many aspects, interpersonal-service task content that refers to interactions of workers with customers is a distinct task characteristic and plays a key role in shifting task demand in the last decades of the US labor market. I also provide novel evidence linking ITI to slower labor productivity growth, while finding no association with ICT revolution. Therefore ITI and RTI reflect the effect of two different types of technical change at the occupation level. ITI appears as a natural candidate to extend the relative stagnancy of services argument, which goes back to Baumol (1967) and Fuchs (1968), into detailed industries and occupations.

Using these empirical facts in a model of structural change with many industries and occupations, I derive all of the results observed for employment and technology discussed above. Moreover, the model allows, both conceptually and empirically, distinguishing routinization, through increasing adoption of computers which has been a key aspect of technological developments in recent decades, from the relatively stagnant nature of interpersonal-service tasks which is possibly related to occupation-specific technology and the changing structure of the economy towards services. This distinction is empirically interesting as the emerging literature on occupational reallocation of labor suggests both type of channels as being responsible from the employment trends in the labor market.

There are directions for future research that can be motivated by the results of this paper. First, given that interpersonal-service tasks play a central role in changing employment demand it is important to quantitatively assess the impact of these tasks in job polarization and structural change separately, which might also require updating the aggregate impact of routinization. Second, while the evidence in this paper is in line with a theory of occupation-specific technical change that is inversely related to interpersonal-service tasks, more direct evidence is needed to disentangle sector and occupation-specific technical change. This last point is particularly important for understanding the role of occupations as the driving unit of structural changes in the labor market.

1.A Tables

Table 1.1: O*NET Interpersonal Tasks

1. Interpersonal-service Tasks
Deal With External Customers
Deal With Unpleasant or Angry People
Deal With Physically Aggressive People
Communicating with Persons Outside Organization
Assisting and Caring for Others
Selling or Influencing Others
Performing for or Working Directly with the Public
2. Within-Firm Interpersonal Tasks
Work With Work Group or Team
Coordinate or Lead Others
Communicating with Supervisors, Peers, or Subordinates
Coordinating the Work and Activities of Others
Developing and Building Teams
Guiding, Directing, and Motivating Subordinates
Coaching and Developing Others

Source: O*NET database.

Table 1.2: Distinctive Features of Interpersonal Tasks: Skill Intensity and Service Specialization

(Dependent Variables: Skill Intensity and Service Sector Intensity)

	A. Skill Intensity				B. Service Sector Intensity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ITI	0.62***	0.06			0.21***	0.11***		
	(0.16)	(0.09)			(0.02)	(0.01)		
Within-Firm Int.			1.04***	0.26***			0.03	-0.05**
			(0.13)	(0.09)			(0.03)	(0.02)
Constant	12.85***	-	12.79***	-	0.63***	-	0.66***	-
	(0.17)		(0.12)		(0.03)		(0.03)	
R^2	0.11	0.76	0.36	0.77	0.34	0.69	0.01	0.64

Notes: The table shows OLS estimates from the regression of dependent variables on different interpersonal measures shown in each row. There are 322 observations in each specification. The variable for skill intensity of an occupation (dependent variable of Panel A) is 1980-2010 long-run mean years of schooling. The variable for service sector intensity of an occupation (dependent variable of Panel B) is 1980-2010 long-run mean occupational employment share of service-sector workers relative to all employment. All regressions are weighted by occupations' 1980 employment shares. Columns (2), (4), (6), (8) include major occupation group dummies, hence constant term is not reported for these specifications. Major occupation groups are listed in Table 1.A.2. Employment shares and dependent variables are computed using 1980 Census and 2010 American Community Survey. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1.3: Partial Correlates of Interpersonal Tasks from DOT

	OLS Coefficients	
	ITI	Within-firm
Intelligence aptitute	-0.07	0.10*
	(0.06)	(0.05)
Data Complexity	-0.05	0.21***
	(0.05)	(0.06)
Creative preference	0.04	0.27***
	(0.07)	(0.07)
Direction, Control, and Planning	-0.04	0.45***
	(0.10)	(0.09)
Dealing with people beyond instructions	0.68***	0.40***
	(0.07)	(0.08)
Talking	0.47***	0.34***
	(0.07)	(0.08)
People Complexity	0.32***	0.29***
	(0.10)	(0.08)
Influencing People	0.29**	-0.04
	(0.14)	(0.11)

Notes: Each value in the table corresponds to a separate regression where right-hand side variable is the interpersonal variable indicated in the column and the dependent variable is the variable from DOT indicated in the row. All regressions are weighted by 1980 employment shares and include dummies for major occupation groups in Table 1.A.2. Robust standard errors are in parentheses. Intelligence aptitude, data complexity, people complexity variables are multiplied by minus one, since higher scores of original measures correspond to lower intensity or complexity of the task attribute. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1.4: Employment Growth of Occupations: Interpersonal-Service Tasks and Alternatives, 1980-2010

(Dependent Variable: Log Change in Total Hours)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ITI	0.39***		0.36***		0.32***		0.43***		0.32***	0.35***	0.20***	0.17**
	(0.05)		(0.06)		(0.05)		(0.07)		(0.05)	(0.07)	(0.05)	(0.09)
RTI		-0.15***	-0.06							-0.09**		-0.04
		(0.05)	(0.04)							(0.04)		(0.05)
Offshorability						-0.15**	0.08			0.12		-0.02
						(0.06)	(0.07)			(0.08)		(0.08)
Years of Education								0.16***	0.10***	0.09***		0.01
								(0.02)	(0.03)	(0.03)		(0.06)
Routine				-0.20***	-0.06*							
				(0.05)	(0.04)							
Manual				0.05	0.02							
				(0.05)	(0.04)							
Abstract				0.18**	0.17**							
				(0.07)	(0.07)							
Occupation Group Dummy	-	-	-	-	-	-	-	-	-	-	✓	✓
R^2	0.23	0.05	0.24	0.18	0.29	0.03	0.24	0.14	0.29	0.30	0.40	0.41

Notes: The table shows the OLS estimates of variables indicated in each row. Dependent variable is the 1980-2010 log change in employment. Employment is defined as total annual working hours computed from Census 1980 and American Community Survey 2010. All regressions are weighted by 1980 employment share that is calculated for each of 322 consistent occupations, which is the number of observations for each specification. Robust standard errors are in parentheses. See the main text for information on task measures. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1.5: Wage Bill Growth of Occupations: Interpersonal-Service Tasks and Alternatives, 1980-2010

(Dependent Variable: Log Change in Total Wage Bill)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ITI	0.45***		0.44***		0.39***		0.52***		0.34***	0.40***	0.21***	0.19**
	(0.06)		(0.06)		(0.06)		(0.07)		(0.06)	(0.07)	(0.06)	(0.08)
RTI		-0.15***	-0.04							-0.07		-0.01
		(0.06)	(0.05)							(0.05)		(0.05)
Offshorability						-0.14*	0.14*			0.15*		-0.02
						(0.07)	(0.08)			(0.08)		(0.08)
Years of Education								0.23***	0.17***	0.16***		0.04
								(0.03)	(0.03)	(0.03)		(0.06)
Routine				-0.20***	-0.04							
				(0.05)	(0.04)							
Manual				0.00	-0.03							
				(0.05)	(0.04)							
Abstract				0.26***	0.24***							
				(0.08)	(0.08)							
Occupation Group Dummy	-	-	-	-	-	-	-	-	-	-	✓	✓
R^2	0.26	0.04	0.26	0.22	0.36	0.02	0.27	0.24	0.37	0.39	0.49	0.49

Notes: The table shows the OLS estimates of variables indicated in each row. Dependent variable is the log change in wage bill for an occupation. Wage bill is defined as total annual wage income computed from Census 1980 and American Community Survey 2010. All regressions are weighted by 1980 employment share that is calculated for each of 322 consistent occupations, which is the number of observations for each specification. Robust standard errors are in parentheses. See the main text for information on task measures. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1.6: Labor Productivity Growth and Tasks

(Dependent Variable: Industrial Log Labor Productivity Index, 1987-2014)

	(1)	(2)	(3)
Time Trend $\times$ ITI	-0.22***		-0.16***
	(0.06)		(0.05)
Time Trend $\times$ RTI		0.61***	0.53***
		(0.12)	(0.14)
R^2	0.61	0.62	0.62

Notes: The table shows OLS estimates of each variable indicated in rows. Observations come from 279 industry categories of BLS labor productivity and cost series from 1987 to 2014. Task scores are calculated for 12 NAICS industries. Number of observations is 5438 in each specification. Time interaction coefficients of task scores are multiplied by 100. Year and industry dummies are used in all regressions. Standard errors clustered by NAICS industry classification are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1.7: Tasks and Technology: Computerization at Occupation Level

*(Dependent Variable: Combined Computerization-Automation Measure from O*NET)*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ITI	-0.05		0.08		0.07		-0.06
	(0.08)		(0.08)		(0.07)		(0.07)
RTI		0.36***	0.38***				
		(0.07)	(0.07)				
RTI Breakdown (DOT)							
Abstract				0.26***	0.26***		
				(0.06)	(0.06)		
Routine				0.19***	0.22***		
				(0.06)	(0.07)		
Manual				-0.40***	-0.41***		
				(0.09)	(0.09)		
RTI Breakdown (O*NET)							
Non-Routine Cognitive:							
Analytic						0.47***	0.43***
						(0.08)	(0.09)
Interpersonal						-0.26***	-0.22**
						(0.07)	(0.09)
Routine:							
Cognitive						0.47***	0.48***
						(0.05)	(0.05)
Manual						-0.01	-0.05
						(0.06)	(0.06)
Non-Routine Manual						-0.50***	-0.48***
						(0.07)	(0.08)
Constant	0.09	0.08	0.07	0.06	0.06	0.02	0.03
	(0.10)	(0.09)	(0.09)	(0.07)	(0.07)	(0.05)	(0.05)
R^2	0.00	0.19	0.19	0.38	0.38	0.64	0.65

Notes: The table shows the OLS estimates of technology measure from O*NET as the arithmetic mean of "interaction with computers" and "degree of automation" variables on each task variable indicated in rows. Dependent variable as well as the independent variables are normalized to have 0 mean and 1 standard deviation. There are 322 observations for each specification. All regressions are weighted by 1980 employment share. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1.8: Tasks and Technology: Industry ICT Intensification *(Dependent Variable: 100 $\times$ ICT Share in New Capital Purchases, 1997)*

	(1)	(2)	(3)
ITI	0.71		1.46
	(2.41)		(2.30)
RTI		8.34***	8.47***
		(2.21)	(2.34)
Constant	34.84***	34.84***	34.84***
	(2.96)	(2.78)	(2.79)
R^2	0.00	0.12	0.13

Notes: The table shows OLS estimates of each task variable that reflects the long-run mean industry task intensity indicated in rows. The dependent variable, ICT share of an industry, is the ratio of the sum of computer, office, accounting, software and communication equipment purchases to all purchases of capital computed from 1997 Capital Flow Table of Bureau of Economic Analysis. Number of observations is 66 in each specification. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1.9: TASKS AND TECHNOLOGY: COMPUTER ADOPTION IN COMMUTING ZONES

(Dependent Variable: Adjusted PCs per Employee in Commuting Zone, 1990-2000)

	(1)	(2)	(3)	(4)	(5)
ITI	0.07**	-0.01			0.01
	(0.03)	(0.02)			(0.02)
RTI			0.16***	0.06**	0.06***
			(0.01)	(0.01)	(0.01)
Skill Intensity		0.19***		0.15***	0.15***
		(0.01)		(0.01)	(0.01)
R^2	0.35	0.62	0.50	0.63	0.63

Notes: The table shows OLS estimates of each task variable that reflects the mean commuting zone task intensity indicated in rows. All regressions include dummies for time and state. Observations come from 675 commuting zones for 1980-1990 and 660 commuting zones for 1990-2000. Number of observations is 1335 in each specification. For construction of commuting zones and PC per employee data see Autor and Dorn (2013). Task scores and skill intensity at the commuting zone level are computed from 1980 Census. Standard errors clustered by state are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1.A.1: Top and Bottom Interpersonal Occupations

A. Interpersonal-Service Intensity (ITI) Rankings

1. Top 15 Occupations	2. Bottom 15 Occupations
Police and detectives	Mathematical Technicians
Correctional Officers	Woodworking Machine Setters, Operators, and Tenders, Except Sawing
Licensed Practical and Licensed Vocational Nurses	Shoe Machine Operators and Tenders
Child, Family, and School Social Workers	Sawing Machine Setters, Operators, and Tenders, Wood
Registered Nurses	Foundry Mold and Coremakers
Parking Lot Attendants	Pressers, Textile, Garment, and Related Materials
Health Educators	Computer Programmers
Clergy	Remote Sensing Scientists and Technologists
Bartenders	Proofreaders and Copy Markers
Animal Control Workers	Prepress Technicians and Workers
Forest Fire Fighting and Prevention Supervisors	Actuaries
Substance Abuse and Behavioral Disorder Counselors	Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic
Travel Agents	Packaging and Filling Machine Operators and Tenders
Pharmacists	Tool and Die Makers
Physical Therapists	Forging Machine Setters, Operators, and Tenders, Metal and Plastic

B. Within-Firm Interactions Intensity Rankings

1. Top 15 Occupations	2. Bottom 15 Occupations
Chief Executives	Barbers
Clergy	Sewers, Hand
Medical and Health Services Managers	Postal Service Mail Carriers
Education Administrators, Preschool and Childcare Center/Program	Pressers, Textile, Garment, and Related Materials
Urban and Regional Planners	Demonstrators and Product Promoters
First-Line Supervisors of Mechanics, Installers, and Repairers	Shoe and Leather Workers and Repairers
Actors	Camera and Photographic Equipment Repairers
First-Line Supervisors of Office and Administrative Support Workers	Automotive and Watercraft Service Attendants
First-Line Supervisors of Construction Trades and Extraction Workers	Forging Machine Setters, Operators, and Tenders, Metal and Plastic
Spa Managers	Textile Knitting and Weaving Machine Setters, Operators, and Tenders
Licensed Practical and Licensed Vocational Nurses	Sewing Machine Operators
Aircraft Cargo Handling Supervisors	Postal Service Clerks
Dentists, General	Shoe Machine Operators and Tenders
Financial Managers, Branch or Department	Door-To-Door Sales Workers, News and Street Vendors, and Related Workers
Advertising and Promotions Managers	Furniture Finishers

Table 1.A.2: Average Task Score Percentile Rank in Occupation Groups

	ITI	Within-Firm	Offshorability	RTI	Routine	Manual	Abstract
Manag/Prof/Tech/ Finance/Public Safety	65	80	46	32	32	45	80
Clerical/Retail Sales	58	42	70	80	61	20	47
Personal Service	66	39	56	42	28	61	28
Production/Craft	40	60	37	42	62	45	69
Machine Operators/ Assemblers	19	34	58	65	69	57	22
Transportation/Costruction/ Mechanics/Mining/Farm	53	40	29	33	52	79	33

Notes: The table shows mean task scores in percentiles (times 100) for each occupation group from Autor and Dorn (2013). Mean scores are computed by weighting according to 1980 employment share of occupations. Employment share is the sum of total hours worked in an occupation divided by total hours worked in the economy. All calculations are weighted by 1980 Census labor supply weights.

Table 1.A.3: Routinization, Offhsoring, and Service Sector Specialization

(Dependent Variable: Service Sector Intensity)

	(1)	(2)	(3)	(4)
RTI	0.02	0.04**		
	(0.03)	(0.02)		
Offshorability			-0.00	0.02
			(0.03)	(0.02)
ITI		0.12***		0.12***
		(0.01)		(0.02)
R^2	0.00	0.70	0.00	0.69

Notes: The table shows OLS estimates of dependent variable on different interpersonal measures shown in each row. Dependent variable is 1980-2010 long-run mean employment of service sector workers relative to all employment in an occupation. There are 322 observations in each specification. All regressions are weighted by occupations' 1980 employment shares. Columns (2) and (4) include major occupation group dummies. Occupation groups are listed in Table 1.A.2. Employment shares and dependent variables are computed using 1980 Census and 2010 American Community Survey. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1.A.4: Changing Task Demand and Within-Firm Interactions

	(1)	(2)	(3)	(4)	(5)	(6)
	A. Δ Log Hours			B. Δ Log Wage Bill		
Within-Firm Int.	0.25***	0.11*	0.02	0.33***	0.18***	0.02
	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.07)
ITI		0.33***	0.32***		0.36***	0.34***
		(0.06)	(0.06)		(0.07)	(0.06)
Years of Education			0.10***			0.16***
			(0.03)			(0.04)
R^2	0.12	0.25	0.29	0.17	0.30	0.37

Notes: The table shows the OLS estimates of variables indicated in each row. Dependent variable is 1980-2010 log change in total hours (Panel A) and 1980-2010 log change in wage bill (Panel B) of an occupation. Wage bill is defined as total annual real wage income computed from Census 1980 and American Community Survey 2010. All regressions are weighted by 1980 employment share that is calculated for each of 322 consistent occupations, which is the number of observations for each specification. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

1.B Figures

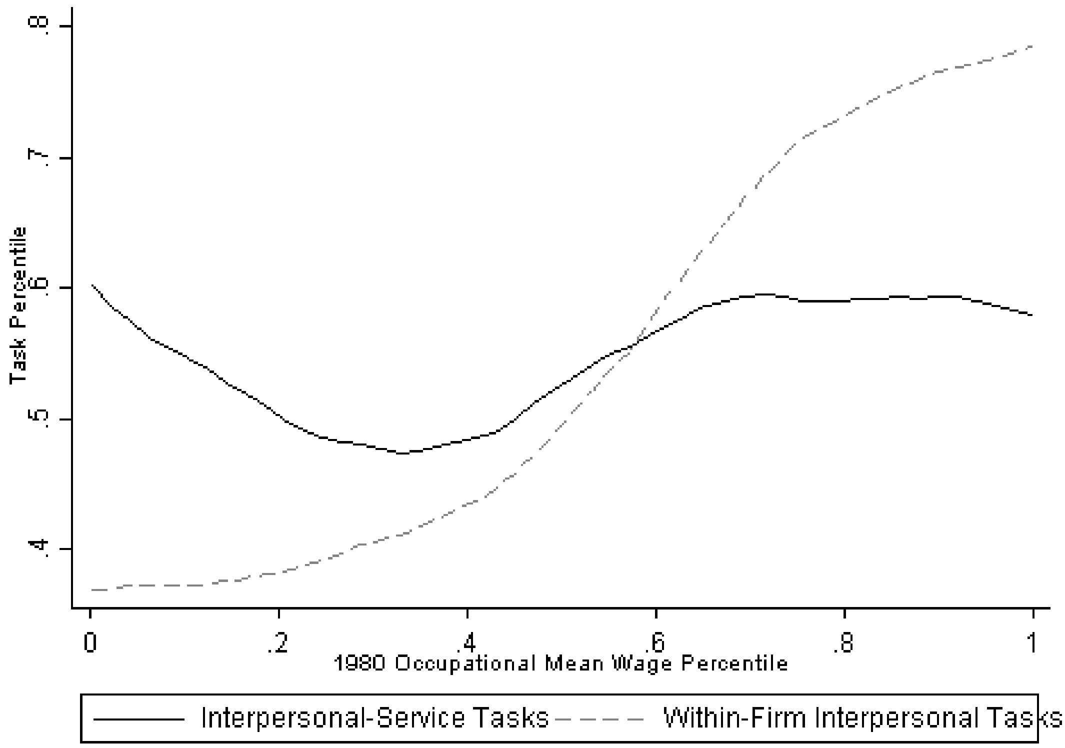

Figure 1.1: Smoothed Interpersonal Task Scores by 1980 Mean Wage Percentile

Notes: The figure shows smoothed occupational task variable percentile rank by 1980 occupational mean wages computed as employment weighted average from 1980 Census. Smoothing is according to a local polynomial using Epanechnikov kernel and default bandwidth of the statistical package.

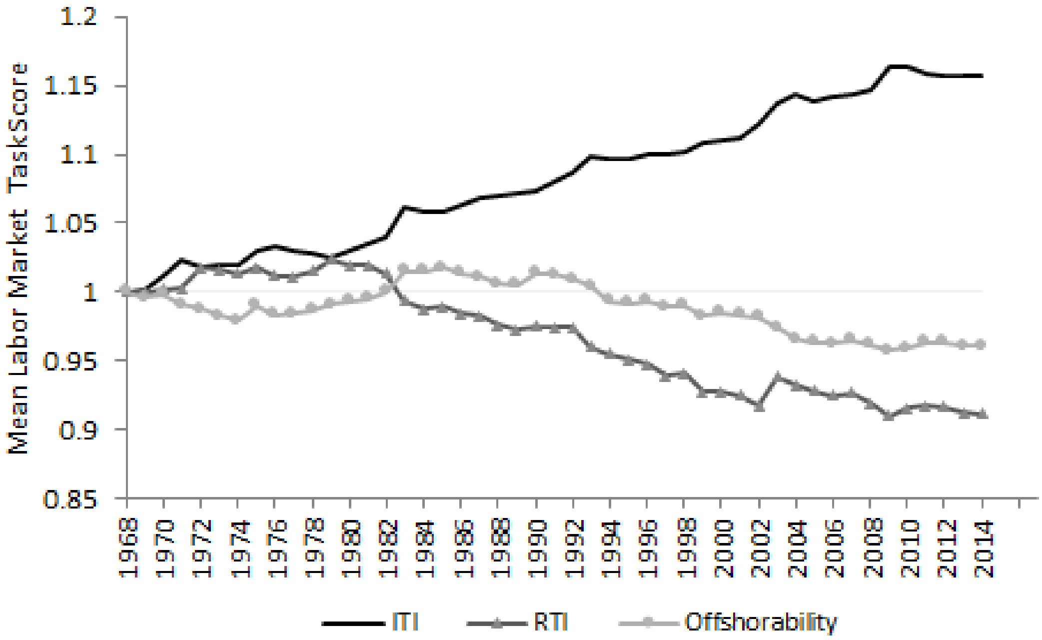

Figure 1.2: Tasks in the Labor Market, 1968-2014

Notes: The figure shows mean task score in the labor market for each year where 1968 score is normalized is one. Mean task score is employment-weighted average percentile rank of time-invariant task scores from O*NET and DOT. Employment weights are from CPS.

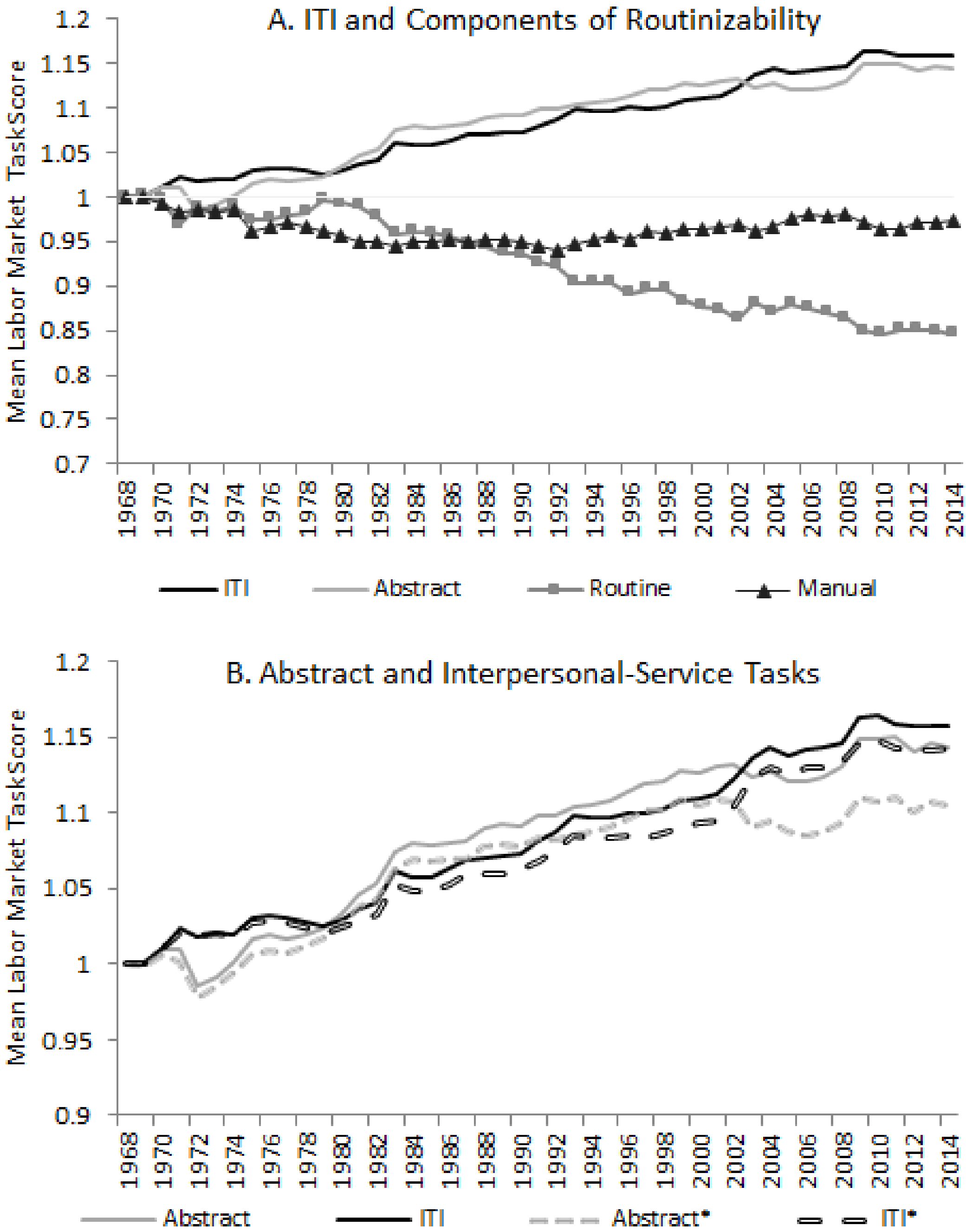

Figure 1.3: The Evolution of ITI and Routinizability in the Labor Market, 1968-2014

Notes: The figure shows mean task score in the labor market for each year where 1968 score is normalized is one. Mean task score is employment-weighted average percentile rank of time-invariant task scores from O*NET and DOT. Employment weights are from CPS. Panel A involves Autor, Levy, and Murnane (2003)'s routine-based classification that is summed into three variables by Autor and Dorn (2013), and the ITI task variable developed in this paper. Panel B focuses on two of them, abstract and interpersonal-service. Abstract* (ITI*) is obtained as standardized residuals from the regression of Abstract (ITI) on ITI (Abstract).

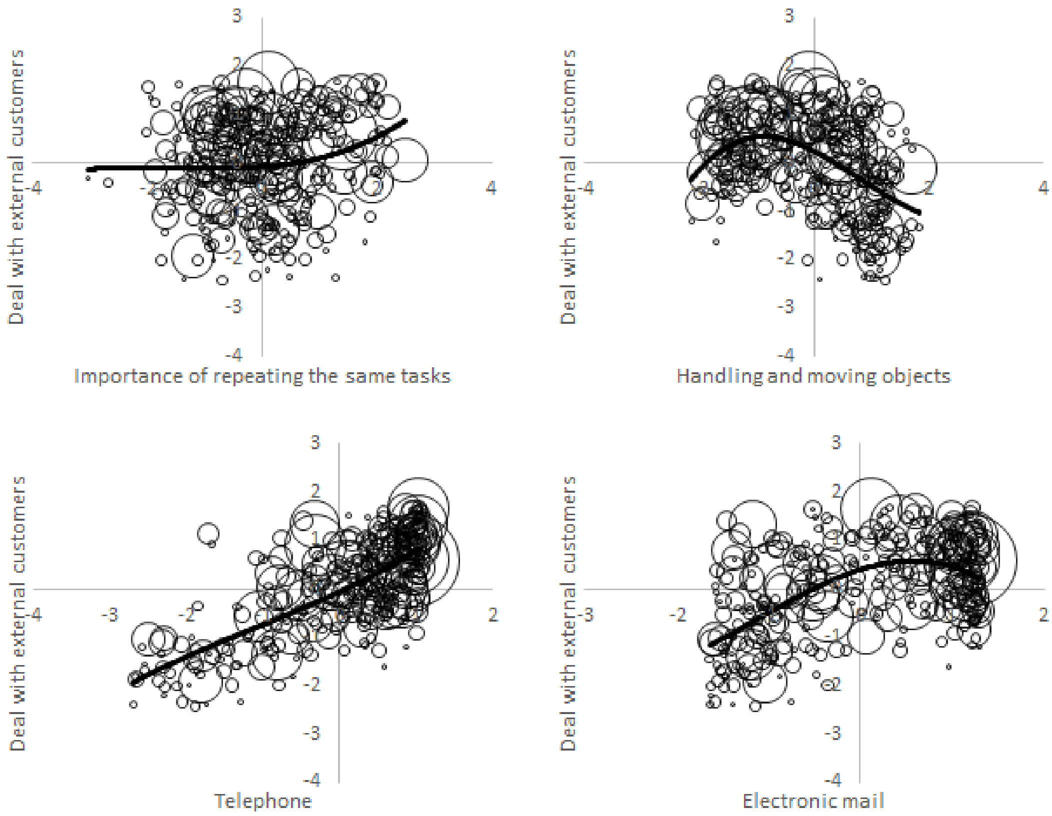

Figure 1.A.1: ITI vs. Elements of Routinization and Offshoring

Notes: The figure plots the proxy ITI measure, "deal with external customers" against the key elements of routinization and offshoring hypotheses. All task variables are directly from O*NET database. Each variable is aggregated to 322 consistent occupations and standardized as explained in the text. Circle size is proportional to the average labor supply weight of each occupation between 1980 and 2010. Solid lines show the fit of a third order polynomial.

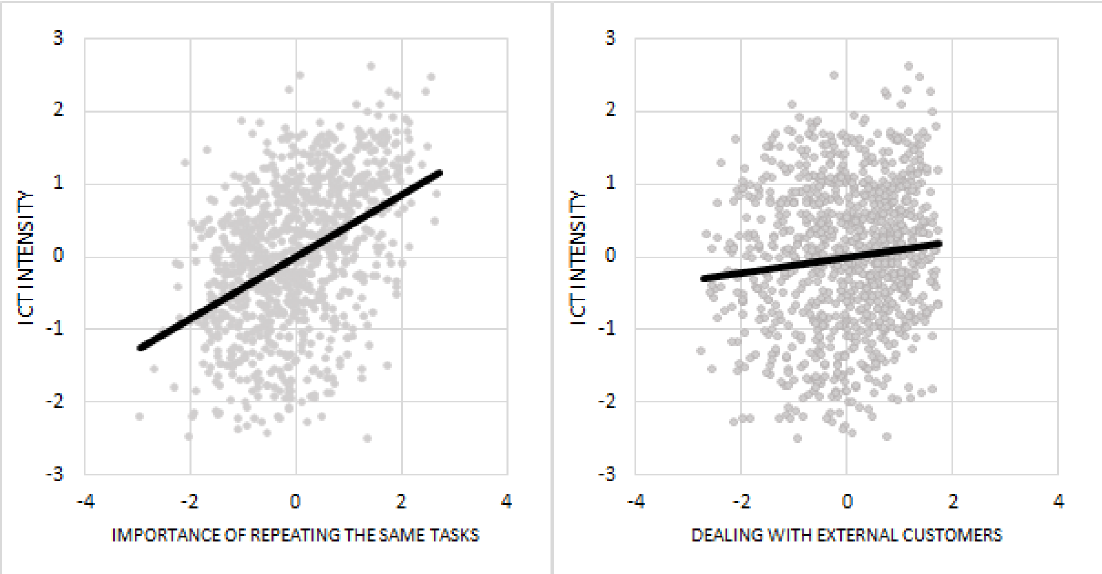

Figure 1.A.2: ICT Intensity and Tasks: Alternative Variables and Detailed Occupations

Notes: The figure plots the ICT intensity measure against alternative task measures for 942 O*NET SOC occupations. All variables reflect importance scores and are standardized to have zero mean and unitary standard deviation. ICT intensity is generated as the mean of two task variables, "interaction with computers" and "degree of automation". Solid lines correspond to the linear fit.

1.C Data Appendix

Census and CPS Data

The Census data cover 1980 Census 5% extract and 2010 American Community Survey. The sample in this study includes workers of age 16-64, employed workers excluding armed forces and self-employed who reported positive wage income. Employment in an occupation is total annual hours worked computed as usual weekly hours times weeks worked variables. Labor supply weights are calculated as annual hours times population weights. Wage bill of an occupation is defined as total annual wage income. Wage income is subject to top-code treatment such that top-coded observations are multiplied by 1.5.

CPS data refer to CPS March extracts. The sample includes workers of age 16-64, employed workers employed workers excluding armed forces, self-employed, and unpaid family workers who reported positive wage income. Employment definition and calculation follow the same steps with the Census data described above.

Data on Productivity and ICT

The data source for labor productivity is BLS labor productivity statistics. Labor productivity is computed as the amount of goods and services produced (output) divided by the number of hours worked to produce those goods and services.[31] The labor productivity indexes used in the study are available for a total of 176 detailed industries.

ICT share in purchases of new capital is calculated using the BEA 1997 Capital Flow Table.[32] BEA reports purchases by capital type for 123 industries. I compute the variable of interest based on an aggregation of 123 industries for establishing consistency with CPS industry definitions.

Occupation level ICT measure follows the procedure for task variables described below. Local labor market level ICT variable is downloaded from David Autor's webpage and all related calculations follow Autor and Dorn (2013).

31 Labor productivity data are available from `https://download.bls.gov/pub/time.series/ip/`
32 Capital Flow Table data are available from `https://www.bea.gov/industry/capflow_data.htm`.

Task Data

There are two sources of task characteristics used in this study. The main source is the Occupational Information Network (O*NET) under the sponsorship of US Department of Labor/Employment and Training Administration. O*NET provides a vast range of task information that are reported at occupation level. I use the July 2014 release of the database downloaded from https://www.onetcenter.org/db_releases.html.

O*NET database provides task information for different scales. I either use the importance scale or the context scale which assign task scores ranging from 1 to 5. The original task variables are reported for 942 O*NET-SOC occupations. I merged these occupations to *occsoc* codes, then match *occsoc* codes to *occ1990dd* using 2010 Census. Then I merged the task scores to *occ1990dd*. At each level of aggregation I use Census labor supply weights. I standardize each task score to have mean of 0 and standard deviation of 1. The derived task scores in the paper computed as means of individual task scores, or sector or labor market wide intensities are standardized in the same fashion.

The second data source on tasks is Dictionary of Occupational Titles (DOT). DOT by Bureau of Labor Statistics is the predecessor of O*NET. The data set I employ comes from England and Kilbourne (1988) who provide information from the "Fourth Edition Dictionary of Occupational Titles" merged into 1980 Census occupation codes through what is known as the TREIMAN file.[33] Using the crosswalk provided by Dorn (2009) and associated labor supply weights, I merged DOT variables into *occ1990dd* codes. Again all variables from this source are standardized in the way described above prior to analyses.

33 The data set is available from http://doi.org/10.3886/ICPSR08942.v2.

Chapter 2

TASK-BASED SOURCES OF JOB POLARIZATION AND STRUCTURAL CHANGE OF EMPLOYMENT IN THE US

Are there any links between the declining labor market importance of the middle-wage jobs (polarization) and the rise of services (structural change) in the recent decades? This chapter estimates a task-biased technical change model and shows that between 1987 and 2014 a substantial portion of occupational and sectoral employment share changes in the US labor market can be accounted for by interpersonal-service tasks, i.e. tasks requiring interactions with customers, and task-routinizability, i.e. the suitability of the task to be replaced by computers. While both task aspects are significant drivers of job polarization, interpersonal-service tasks stand out in explaining the growth of service sector. The results imply a key role for task-specific technical change compared to sector-specific technical change in driving the disaggregate employment trends. I also observe that the negative impact of task-routizability on employment demand changes vanishes for the post-2000 period, suggesting that most of the contribution of routine-biased technical change to job polarization took place during 1990s.

2.1 Introduction

The occupation and sector structure of employment in advanced economies evolve on the back of two trends in recent decades: job polarization and structural change. Job polarization refers to declining employment shares of occupations that are intensively found in the middle of wage distribution as opposed to rising shares of occupations at both tails, and is observed in the US (Autor and Dorn, 2013; Autor, Katz, and Kearney, 2006), UK (Goos and Manning, 2007), Germany (Spitz-Oener, 2006), and many European economies (Goos, Manning, and Salomons, 2009, 2014; Michaels, Natraj, and Van Reenen, 2014) after 1980s. Recent evidence suggests that polarization in the labor market might have started as early as the 1950s (Barány and Siegel, 2017). Structural transformation literature documents the declining employment share of agriculture and manufacturing relative to service sector throughout the world with the course of economic development (Herrendorf, Rogerson, and Valentinyi, 2014; Kuznets, 1957; Maddison, 1980).[1,2] The two trends are equally important in shaping the structure of employment. In the US between 1987 and 2014 around 11 percent of occupational employment, and 9 percent of sectoral employment reallocated out of middle-wage occupations and non-service sector, respectively.[3] In this paper I aim to quantify the task-based sources of the two labor market trends.

Two particular task aspects are key in this paper. Customers are embedded in the production process of interpersonal-service tasks and intense interactions with them severely limit the adoption of technologies due to costs associated with customers' satisfaction and capabilities. On the other hand, tasks that are easily codified benefit more from the increasing use of computers in the workplace. These task attributes can affect employment dynamics, since changes in relative productivities in occupations and industries lead to reallocation of employment (e.g., Goos, Manning, and Salomons, 2014; Ngai and Pissarides, 2007). In Chapter 1 of this thesis I introduce interpersonal-service tasks as the key task attribute characterizing service activity and

1 The literature also shows that trends in expenditure and value added shares follow the same pattern (see, e.g., Herrendorf, Rogerson, and Valentinyi, 2014). In this paper I only focus on the structural change of employment.

2 The employment share of manufacturing and services were rising together before the second world war. From then on structural change at broad sector level boils down to the growth of service sector relative to non-service sectors (see, e.g., Ngai and Pissarides, 2008).

3 Based on my own calculations using CPS data. See Table 1 and 2 for occupation and sector classification, respectively.

the changing structure of occupation employment.[4] In addition, the leading explanation of job polarization is routinization (e.g., Autor, Katz, and Kearney, 2008; Autor and Dorn, 2013). This is the first paper that brings together these two task attributes to estimate their impact on labor demand changes based on a model that enables separating sector-specific and occupation-specific technical change.

I build on a simplified version of the occupational structural change model suggested in Chapter 1 where occupations intensive in interpersonal-service content and those with lower levels of routinizability are subject to slower labor productivity growth.[5] Given the imperfect substitutability between the industry output in consumption, and between the task input in production, employment shifts into sectors and occupations that employ interpersonal-service tasks more and routinizable tasks less intensively. While sector employment changes are fully driven by occupation-specific labor productivity as a combination of the two task aspects, reallocation of employment across occupations is affected both by occupation and sector task intensities.

The paper follows the estimation strategy of Goos, Manning, and Salomons (2014). Using employment and industry data for the US between 1987 and 2014, I estimate the conditional labor demand of the model at sector-occupation level and confirm that interpersonal-service tasks and routinizability are two significant channels of changing employment demand. Employment share predictions based on the estimated impacts of task measures and elasticities from model's equations suggest that the model can explain substantial part of occupational and sectoral change in employment shares. The model strikingly implies that roughly two thirds of the predicted job polarization and nearly all of the predicted service sector growth is explained by interpersonal-service tasks. On the other hand, routinization has a limited impact on job polarization and seems to play a negligible role in driving structural change.

There are two additional contributions of the paper. First, my results suggest that most of the changes in the employment structure is task-specific rather than sector driven. Estimating conditional labor demand growth under sector-occupation struc-

4 I also show in Chapter 1 that interpersonal-service tasks exhibit different characteristics with respect to within-firm interpersonal interactions, non-routine cognitive interpersonal tasks and non-routine manual tasks. Moreover, interpersonal-service tasks are essentially unrelated to ICT intensification. Overall, the evidence suggests that customer-oriented interpersonal interactions cannot be adequately characterized within the existing task frameworks studied in the literature.

5 Baumol (1967), Fuchs (1968) and Chapter 1 argue that ITI limits productivity growth due to the presence of customers during the production process; (among others) Autor, Levy, and Murnane (2003), Autor and Dorn (2013) and Goos, Manning, and Salomons (2014) associate routinization with higher productivity growth as a result of the use of cheaper ICT.

ture allows for disentangling task-specific demand shifters from sectoral ones.[6] Labor demand estimations augmented with sector-time fixed effects, and broad and detailed sector-specific growth rates suggest that the estimated task-based growth is not significantly affected by sector-specific factors and trends. Therefore the model's task-based perspective with respect to the source of technical change, and consequently, the reallocation of employment across occupations and sectors by task-specific forces appear to be a valid representation of disaggregate employment trends in the economy.

Lastly, I observe that routinization has a big impact on employment demand changes during the 1990s which completely disappears after 2000 as opposed to the relatively stable impact of interpersonal-service task intensity in both periods. If routine-biased technical change operates through a greater transmission of falling computer prices in more routinizable occupations[7], this finding implies that the price of computers should have declined a lot less after the 2000s. As a matter of fact, the official statistics indicate substantial slowdown in the falling relative price of computers during mid-2000s (Gordon, 2015). Estimating the model for different time periods suggests bulk of the effect of computers in the occupational employment structure was realized in the 1990s, in line with the literature on polarization (Autor, Katz, and Kearney, 2008; Autor, Katz, and Kearney, 2006).

The paper is closest to Chapter 1 of this thesis. By estimating the task-based model, I complement Chapter 1 with answering two important questions it does not address. First, whether the observed predictive success of the task intensities on occupation employment persists when the industry structure is explicitly taken into account. The second answer is on the relative importance of different tasks in jointly understanding the trends in occupation and sector employment.

This paper is also closely related to Goos, Manning, and Salomons (2014). There are three differences between this paper and theirs. First, I study the US economy whereas their analysis covers 16 countries in Europe. Second, they explore the role of routinization and offshoring while I also study the impact of the novel task dimension

6 In the emerging literature that combines structural change and polarization, the basis of technical change is not clear. Trends in occupational and sectoral employment can be qualitatively explained both by sector-specific technical change (Barány and Siegel, 2017), and occupation-specific technical change (Duernecker and Herrendorf, 2017), given patterns in occupations' sectoral specialization.

7 The idea is first employed in this context by Autor and Dorn (2013) for the special case where there is a routine occupation that is affected by falling computer prices and a non-routine one which is not affected at all. Goos, Manning, and Salomons (2014) extend the idea so that occupations effectively face different declines in the price of capital input proportional to their routinizability.

of interpersonal-service tasks.[8] Last, I compute the impact of task measures on employment reallocation across sectors and occupations while their analysis is confined to employment share changes across occupations and their shift-share decomposition.

Lee and Shin (2017) provide an analysis similar to this paper in the sense that they also study an economy with occupation-sector structure in the labor market and assess the impact of task-specific technical change. By calibrating occupation-specific TFP rates in their model they argue that faster productivity growth in middle-wage occupations not only drives polarization but also capable of explaining the structural change. This paper supports their result that a task-based model is capable of explaining both trends. In addition, while the calibration exercises cannot rule out the hypothesis that all of the growth of services is driven by sector-specific productivity growth, the sector-fixed effects estimation strategy employed here assures that the predictions of the task model, which can explain almost all of the service sector employment change, is free from sector-specific factors. They show that the occupation-specific productivity growth rates are in line with measures of routinization, and hence indirectly relate the model's performance to routinizability.[9]

The paper is related to others that reconcile both important employment trends by emphasizing the role of services in the economy. Barány and Siegel (2017) suggest differential sector-specific productivity growth as the main driver of both structural change and polarization, which contrasts with the results of this paper. Duernecker and Herrendorf (2017) argue that occupation-specific technical change, rather than sector-specific, that occurs at a slower pace in service occupations can lead to both trends. While my results support their view, the approach of this paper can be seen as an extension of their binary service occupation classification.

This paper provides evidence in favor of others in bringing out the importance of task-specific nature of technological and structural changes in the labor markets (e.g., Acemoglu and Autor, 2011; Autor, Katz, and Kearney, 2006; Autor, Levy, and Murnane, 2003; Goos and Manning, 2007), while suggesting a more limited role for routinization for the US case.

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8 I leave out offshoring in the analysis following the growing evidence on its poor performance with respect to predicting occupational employment demand changes (Autor and Dorn, 2013; Goos, Manning, and Salomons, 2014; Lee and Shin, 2017, and Chapter 1 of this thesis). Nevertheless, I confirm, by estimating the model of this paper using an offshoring measure, that unlike interpersonal tasks and routinization, offshoring alone is not a major factor in explaining changes in employment shares of occupations and sectors.

9 In particular, Lee and Shin (2017) argue that routine manual and non-routine interpersonal measures of Acemoglu and Autor (2011) display high correlations with task-specific TFP rates.

The rest of the paper is structured as follows. I introduce the analytical model used to estimate conditional demand for labor and sector output in the next section. Section 2.3 performs estimations of key demand equations of the model. Then it provides occupational and sectoral employment share predictions by task attributes and evaluates the performance of the model. I conclude the paper in Section 2.4.

2.2 Analytical Framework

In this section I outline a general equilibrium model suitable for empirical analysis of structural change and job polarization together. The model is a simplified version of the one introduced in Chapter 1 of this thesis. Here I assume that labor is the only input of production and hence there is no accumulation of capital. I briefly introduce the model below and characterize the equilibrium.

2.2.1 Production Technology

Sector output is produced by perfectly competitive firms which combine task inputs from occupations. The output of each sector is then consumed by the household. There are I sectors and J occupations in the economy. The production follows the following CES functional form at each period t:

$$Y_{it} = \left[\sum_{j}^{J} (\phi_{ij})^{\frac{1}{\theta}} (A_{jt} L_{ijt})^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}, \tag{2.23}$$

where $i = 1, \ldots, I$; $j = 1, \ldots, J$; Y_{it} is output in sector i; L_{ijt} is sector i's labor input from occupation j; A_{jt} is occupation-specific technology; ϕ_{ij} is exogenous task weight; and $\theta > 0$ is the elasticity of substitution between task inputs, which is assumed to be the same across sectors. The sector output is produced by combining several task input, each of which are performed by the labor of a particular occupation using the occupation-specific technology.[10] The level and growth rates of an occupation's technology can change depending on the nature of the task content of the occupation.

10 Here the task is defined at the occupation level as the set of required small pieces of work that define an occupation.

Firms take sector output price, p_{it}, as given and maximize profits:

$$\max_{T_{ijt}} \left[p_{it} Y_{it} - \sum_{j}^{J} w_{jt} L_{ijt} \right], \tag{2.24}$$

where w_{ijt} is the wage rate. I abstract from Roy-type occupation-specific worker skill or preference heterogeneity and assume perfect mobility across industries and occupations, hence there is a single wage rate w_t in the economy.

First order conditions imply the following demand for labor conditional on sector output, output price (equal to maginal cost), and wages:

$$L_{ijt} = \phi_{ij} A_{jt}^{(\theta-1)} \left(\frac{p_{it}}{w_{jt}} \right)^{\theta} Y_{it}. \tag{2.25}$$

2.2.2 Households

The representative household in this economy consumes the goods produced by sectors, C_i for $i = 1, \ldots, I$, and has the following utility in each time t:

$$\log C_t, \tag{2.26}$$

where $C_t = \left(\sum_i^I (\lambda_i C_{it})^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{\epsilon}{\epsilon-1}}$ is the CES consumption aggregator. $\epsilon > 0$ is the elasticity of substitution between goods, and λ_i is a preference weight of the consumer to good i. Consumers maximize utility by choosing the optimal saving and consumption subject to the following budget constraint:

$$\sum_i^I p_{it} C_{it} = M_t. \tag{2.27}$$

The left hand side of the budget constraint is the total expenditure on consumption. The right hand side, M_t, is the total household resources that simply amounts to labor income in this economy.

First order condition for the optimal consumption is given by the following:

$$C_{it} = \lambda_i^{\epsilon-1} \left(\frac{p_{it}}{P_t} \right)^{-\epsilon} C_t, \tag{2.28}$$

where the price index, P, is given by

$$P_t = \left[\sum_i^I \left(\frac{p_{it}}{\lambda_i} \right)^{1-\epsilon} \right]^{\frac{1}{1-\epsilon}}. \tag{2.29}$$

2.2.3 Equilibrium

For all $t \geqslant 1$, given occupation-specific technology for each occupation $\left\{A_{jt}\right\}_{i=1}^{J}$, equilibrium in this economy is defined by industry output prices $\{p_{it}\}_{i=1}^{I}$, wage rate w_t; consumption bundle $\{C_{it}\}_{i=1}^{I}$, sector output $\{Y_{it}\}_{i=1}^{I}$, labor allocated to each occupation in each sector $\left\{\left\{L_{ijt}\right\}_{j=1}^{J}\right\}_{i=1}^{I}$ such that:

1. Households maximize utility in (2.26) subject to (2.27) by choosing how much to consume from each sector output,
2. In each sector firms maximize profits according to (2.24),
3. Markets clear:
   a) $C_{it} = Y_{it}$ for $i = 1, \dots, I$,
   b) $L_t = \sum_{i=1}^{I} \sum_{j=1}^{J} L_{ijt}$.

Sector output prices are pinned down by the following equation:

$$p_{it} = \left(\sum_j^J \phi_{ij} \left(\frac{w_t}{A_{jt}} \right)^{1-\theta} \right)^{\frac{1}{1-\theta}}, \tag{2.30}$$

2.2.4 Evolution of Technology

I assume that occupation-specific technology A_{jt} follows a growth trajectory that is potentially a linear combination of several orthogonal task characteristics:

$$\log A_{jt} = \gamma_t + \sum_{x \in X} \gamma_x x_j \times \mathtt{trend}, \tag{2.31}$$

where γ_t is the time-specific effect on technology that captures general technology shocks, γ_x is the task-specific growth factor of the task aspect x in a set of tasks X; x_j is the time invariant task score for occupation j; and $\mathtt{trend}$ is the linear time trend.

In particular, I characterize the evolution of technology by interpersonal-service task intensity (ITI) and routinizability (RTI). Hence occupation-specific technical change follows:

$$\log A_{jt} = \gamma_t + \gamma_{ITI} ITI_j \times trend + \gamma_{RTI} RTI_j \times trend. \tag{2.32}$$

Higher ITI occupations are relatively harder to be restructured to benefit from organizational and technical developments due to the complexity of direct interactions with customers. Independently, advances in computing technology trigger greater technical improvements in occupations that are characterized by higher RTI. Therefore I expect that $\gamma_{ITI} < 0$ and $\gamma_{RTI} > 0$.

2.3 Accounting for Job Polarization and Structural Change

In this section I evaluate the impact of task-based sources of technological change on job polarization and structural change in the US labor market between 1987 and 2014. Using annual data on occupations and sectors, I first estimate the conditional labor and output demand equations implied by the model. This enables not only comparing the direct effect of task measures on labor demand, but also assess the relevance of the model and some of its predictions. Then I calculate the contributions of each task variable on the changes of employment share for each occupation and sector and evaluate the predictive performance of the model.

2.3.1 Data

In order to perform the analysis I bring together employment data at occupation and sector level, sectoral measures of output, costs and prices, and data on occupational tasks. Below I briefly describe the data used in this section.

Sector and Occupation Classification

The unit of analysis is sector-occupation. Sector classification is based on BEA's NAICS *sectors* in value added tables, which are 13 industry groups in total.[11] For occupations I use a modified version of 2 digit SOC codes in order to increase comparability with Goos, Manning, and Salomons (2014) who perform a similar analysis for European Countries based on International Standard Classification of Occupations (ISCO) as well as to increase model's sensitivity to occupations. The analysis utilizes 20 occupation groups in total.[12] Occupations and sectors are listed in Table 2.1 and 2.2.

Employment Data

I use 1987-2014 waves of CPS data at annual frequency. The measure of employment is total annual hours. Each sector and occupation group is manually mapped using consistent detailed industry and occupation categories of CPS. Then for each industry-occupation group of this study, I calculate total employment as total annual hours adjusted by population weights.

Sector Output and Costs

The source of sector output data is BEA's GDP by Industry Accounts. Output is calculated by dividing production, which is industry value added index, by the corresponding industry price index. I also use industry marginal costs as an alternative to output value added price indexes. Industry marginal costs are measured by a variable that is calculated in two step. First, net operating surplus is subtracted from industry value added. Then the difference is divided by the output measure. Net operating surplus is derived from GDP by Industry Components Table as gross operating surplus minus consumption of fixed capital.

Task Data

The sources of task data are O*NET and the Dictionary of Occupational Titles (DOT), which are the two main references for occupational task attributes. ITI combines 7 variables in work context and work activities categories of O*NET in order to measure

11 The analysis excludes agriculture and government sector.
12 Agriculture occupations are also dropped from the sample.

customer oriented interpersonal interactions.[13] Task-routinizability is measured by the RTI variable of Autor and Dorn (2013). RTI is constructed by combining the abstract, routine and manual task measures of Autor, Levy, and Murnane (2003) using DOT.

For this analysis the task measures for 322 detailed consistent occupations of Dorn (2009) are merged into broader occupation groups of this study. Occupation group mean task scores are computed over the sample period using labor supply weights, i.e., annual hours times CPS weights. The measures are standardized in order to have zero mean and unitary standard deviation.

2.3.2 Summary: Trends in Employment, and Tasks

The summary of employment changes and mean task scores for occupations and sectors are reported in Tables 2.1 and 2.2. Table 2.1 summarizes occupations in three broad categories, following the job polarization literature. In order to emphasize job polarization, occupations in Table 2.1 are ranked according to mean hourly wages. Panel A of Table 2.1 clearly outlines job polarization: Between 1987 and 2014 high-wage occupations increase their employment share by about 8 and low-wage jobs roughly by 3 percentage points. A related and interesting observation is the homogeneity in the sign of employment share changes within each wage group. The only exceptions are community and social service workers, and drivers in the middle-wage group.

Similarly, Panel A of Table 2.2 summarizes level and changes in employment demand across industries for the same period. Service sector employment growth to a large extent develops through education, health-care and social assistance industries. The wholesale industry is an outlier in the service sector with employment share loss of 2 percentage points. Manufacturing sector accounts for about 60% of employment, and almost all of the contraction in employment share, in goods producing sector.

Table 2.1 and 2.2 also provide information about mean ITI and RTI scores for occupation and sectors. Panel B of Table 2.1 suggests two observations regarding average task intensities for occupations. First, general tendency of the two task measures con-

13 ITI consists of the following task attributes: deal with external customers, deal with unpleasant or angry people, deal with physically aggressive people, communicating with persons outside organization, assisting and caring for others, selling or influencing others, performing for or working directly with the public.

trasts across broad occupation groups such that high- and low-wage jobs on average have higher ITI and lower RTI while middling occupations on average display low ITI and high ITI score. On the other hand, within each part of the wage distribution ITI and RTI are not correlated. Some high-wage occupations such as engineering and technician jobs have low ITI scores, and others such as the legal category score high in RTI.[14] For sectoral averages a different picture emerges (Panel B of Table 2.2). While goods (service) sector is specialized in low (high) ITI tasks, both sectors have moderate levels of routinizability. Service sector is slightly more routinizable compared to goods. Similar to occupations, industries overall do not exhibit significant correlation between the two task measures.

The summary tables give initial indication of the association between task scores and change of employment demand. Greatest increases in occupation and industry employment shares coincide with a high score of ITI and low score of RTI, and vice versa. For instance, among high-wage occupations managerial and health-care jobs attract highest share of employment, and both are high-ITI and low-RTI jobs. In the middle of wage distribution, machine operators go through the largest loss in employment share. Unsurprisingly this group is highly routinizable and non-interpersonal-service intensive. From the lens of industries, a similar association can be made between task scores and structural change of employment. The most remarkable flows of employment are observed from manufacturing industries which are specialized in routine and non-interpersonal-service tasks to education, health and social assistance industries which have the opposite tendency in terms of average tendency of tasks.

The tables also suggest that employment share changes are associate with a given task score also conditional on the other. Two examples are instructive. Considering the high RTI score that ranks the second after office and administrative occupations, one would expect a sharp decline in employment share of legal occupations. However, legal occupations rank also high in ITI and in fact, end up with a higher employment share in 2014. A declining emloyment share of mechanics and repairers, which are highly manual intensive occupations and consequently score low in RTI, is more consistent with the lack of interpersonal-service interactions.

Regardless of how insightful they are, information from these tables can provide only an incomplete characterization of the connection of task characteristics to the changing structure of employment. The next section, guided by the theoretical frame-

14 The overall correlation coefficient between ITI and RTI is -0.08.

work introduced above, explores how task characteristics are related to the evolution of employment demand in the disaggregate parts of the economy.

2.3.3 Estimation and Results

2.3.3.1 *Labor Demand Estimation*

I use the model's implied equations in order to estimate the impact of task measures on labor demand. In particular, I estimate labor demand equation conditional on industry output and marginal costs. Labor demand is given by equation (2.25). The following shows the log of labor demand:

$$\log L_{ijt} = -\theta \log w_t + \log \phi_{ij} - (1-\theta)\log A_{jt} + \theta \log p_{it} + \log Y_{it}. \quad (2.33)$$

The model does not feature worker heterogeneity and assumes a perfectly competitive labor market. Therefore wages equalize for all workers in all occupations and industries. The wage of the model is not a direct counterpart of the wages in the data, given substantial variation of wages and wage growth across occupations. Therefore I control wages with time and sector-occupation fixed effects in the empirical model. Imposing the model's assumptions on technology and the fixed effects I get the following estimable labor demand equation:

$$\begin{aligned} \log L_{ijt} &= \zeta_{ij} + \zeta_t + \theta \log p_{it} + \log Y_{it} \\ &\quad - (1-\theta)\gamma_{ITI} ITI_j \times trend - (1-\theta)\gamma_{RTI} RTI_j \times trend, \end{aligned} \quad (2.34)$$

where ζ_{ij} and ζ_t represent fixed effects for sector-occupation and time, respectively.

Table 2.3 presents the estimates of labor demand for 260 sector-occupation pairs from 1987 to the end of 2014. Columns (1)-(4) estimate conditional labor demand subject to the restriction that the coefficient of sector output is 1, as the model suggests. The last column shows the estimated coefficients when the restriction is not imposed.

Column (1) indicates that conditional on sector output and marginal costs, an occupation with one standard deviation larger ITI is subject to around 0.7 percentage points higher growth in employment each year. Column (2) suggests that an occupation that is one standard deviation more routinizable grows nearly 0.4 percentage points slower each year. Column (3) is the specification suggested by the model since it includes both task attributes. Estimated impacts of ITI and RTI on labor demand growth change only little when estimated jointly.

In the model sector marginal costs equal their price due to perfect competition. However, in reality these prices might differ both in levels as well as in terms of changes between periods. In order to see how much the choice of sector price affects task estimates, column (4) uses value added prices instead of marginal costs. The differences of task estimates between column (3) and (4) are small and statistically insignificant. The coefficients of marginal cost and prices are also similar, indicating that model's simple view on the market structure does a god job.

I report the estimation results the model without the restriction on sector output's coefficient in Column (5). The estimate on sector output shrinks to 0.86 and is precisely estimated. Moreover the task coefficient estimates are nearly identical to those in column (3). Column (5) also enables a formal test of model's assumption of one to one relationship between sector output and conditional labor demand. With a standard error of 0.11 the estimated coefficient is not significantly different from unity.

2.3.3.2 *Occupation-specific vs. Sector-specific Technical Change*

The model assumes that all technical change operates at the level of occupations. On the other hand, most models of structural change solely focus on aggregate sector employment. If there is sector-specific technical change and sectoral specialization of occupations are significant then the results reported in Table 2.3 could be an artifact of reallocation of employment across sectors, which makes sector-specific technical change an important alternative channel to be addressed.

This can be easily illustrated by studying a hybrid version of the model with technical change occurring both at sector and occupation level. For our purposes it is sufficient to add a sector-specific technology term, A_{it}, to the existing model. In this case, the sector production function becomes:

$$Y_{it} = A_{it} \left[\sum_{j}^{J} \left(\phi_{ij}\right)^{\frac{1}{\theta}} \left(A_{jt} L_{ijt}\right)^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}} . \tag{2.35}$$

First order conditions of the firm problem implies that the labor demand equation of the hybrid model is the same except that now it includes a term for industry technology:

$$\begin{aligned}\log L_{ijt} &= -\theta \log w_t + \log \phi_{ij} - (1-\theta) \log A_{jt} + \theta \log p_{it} + \log Y_{it} \\ &- (1-\theta) \log A_{it} \end{aligned} \quad (2.36)$$

The last component of the summation in (2.36) reflects an additional factor on reallocation of labor: conditional on industry output and prices, employment growth rate is greatest in the industry with the slowest technology growth provided that tasks are poor substitutes in production ($\theta < 1$).

Absence of the industry-specific technology in estimation of (2.34) can yield misleading estimates for task coefficients if technical change really happens at the industry level. The bias from the omitted technology term will be greater if certain industries particularly specialize in specific tasks.

Table 2.4 presents the results of various attempts to disentangle occupation-specific growth factors from sector-specific ones. First, I add sector-year fixed effects to the regressions which capture the impact of potential industry-specific and time varying technology as well as sector output and marginal costs. Therefore this strategy also has the additional benefit of limiting the potential biases on task estimates coming from the association of marginal cost growth with occupation-specific technical change.

The results are reported in columns (1)-(3). Comparing the estimates of task coefficients under these columns respectively with those of Table 2.3 clearly suggests that the estimated impacts are not driven by potential sector-specific technology growth.

As an alternative to industry-time fixed effects, I report the estimates of task coefficients when sector-specific time trends are included in the estimation. This reflects that sector-specific technology is modeled to grow linearly with potentially differing slopes across sectors. In particular, I estimate two versions in the remaining columns of Table 2.4. First is differential sector-specific technology growth at the broad sector level estimated by adding an interaction of service sector dummy with time trend. According to column (4), occupations in service sector grow on average 0.26 percentage points faster compared to occupations in the goods sector, but the estimated effect is insignificant. Columns (5) to (7) show that task estimates are similar to regressions with full set of fixed effects shown in the first three columns.

The second version of sector-specific technology growth is reflected in the regression model by adding time trend interactions of detailed sector category dummies. Columns (8)-(10) reports again very similar results compared to other specifications in Table 2.4 and those in Table 2.3.

2.3.3.3 *The Role of Tasks in The Evolution of Employment Demand in 1990s, and 2000s*

I model occupation-specific technical change as a combination of linearly growing ITI and RTI related parts. While this approach, in general, is practical to estimate the long-run average impact of different channels of technology in the labor market (e.g., Katz and Murphy, 1992), there are reasons for doubting the linearity assumption.

The US economy during the sample period has been marked by different phases of technical changes, especially in terms of the impact of computers. The literature documents that during 1990s, and especially through the last 5 years of the decade, labor productivity growth surged on the back of ICT intensive industries. On the other hand, this impetus did not live long. After mid-2000s the aggregate productivity growth as well as those sectors with high ICT use significantly regressed. A reflection of slowing productivity growth of ICT is thought to be tracked in the relative price of computers after early 2000s (Gordon, 2015).

In order to check the stability of the estimates in different parts of the sample, I run conditional demand estimation by splitting the sample into two from the end of 2000. Columns (1)-(3) and (4)-(6) of Table 2.5 report the task coefficient estimates for the two consecutive 13 years of the sample. The estimates for RTI is negative, large and statistically significant before 2000, while they are small and insignificant for the following sub-period. The vanishing impact of RTI on employment demand growth is consistent with the view that the routinization operates through declining relative price of ICT capital and consequently, faster productivity growth in occupations of higher RTI. Therefore most of the impact of routinization on the labor market took place during 1990s when productivity growth due to ICT was remarkable and the relative price of ICT capital was decreasing at an increasing rate.

For ITI, however, the change in the estimated effect on employment growth between the sub-periods is small and statistically insignificant, suggesting that the impact is more homogeneously distributed across time. Considering the fact that ITI reflects the service content at the task level, the stable growth of employment towards more interpersonal-service intensive employment seems to be in line with the continuous growth of services in the economy.

2.3.3.4 *Industry Demand Estimation*

In order to quantify the full effect of task measures in occupational and industrial employment reallocation, one needs to take into account the demand effects on sector output in general equilibrium. Since sectors with high RTI and low ITI exhibit faster productivity growth, relative prices in these sectors fall, affecting the demand for final output from consumers. In particular, elasticity of substitution across sector output, ϵ, is a key parameter for understanding the shifts of labor demand. Inspection of equation (2.28) suggests that if sectoral elasticity of substitution is smaller (greater) than one, relative demand for a sector increases (decreases) following a rise in its relative price. I estimate the parameter through the following equation:

$$\log Y_{it} = \tilde{\gamma}_i + \tilde{\gamma}_t - \epsilon \log\left(\frac{p_{it}}{P_t}\right), \tag{2.37}$$

which is log-transformed and market clearing imposed version of equation (2.28) with industry output consumption weights and aggregate real income captured by industry- and time-fixed effects $\tilde{\gamma}_i$ and $\tilde{\gamma}_t$.

As in the labor demand estimation, I provide the estimation of equation (2.37) using the two sector price measures of value added prices and marginal costs. Table 6 reports the output demand estimation. Column (1) uses sectoral value added price indexes from BEA. The data go back to 1947 and column (1) suggests a postwar elasticity of substitution of 0.52. In order to have sample period compatibility with conditional labor demand estimation, column (2) narrows the time span to start from 1987, with estimated elasticity of 0.45. Column (3) uses the constructed marginal cost measure, which is available starting with 1987. It suggests the elasticity parameter as 0.49, which is remarkably close to value added price's coefficient. These estimates suggest that detailed industry output are poor substitutes, i.e. $\epsilon < 1$.

2.3.4 Growth Accounting of Employment Demand

Using the impacts of task measures and elasticity coefficients estimated by the model, I compute the contributions of task components on the employment share changes of occupations and sectors. This not only allows assessing the predictive power of the model regarding long run employment demand shifts, but also evaluating relative role of task measures and associated technology change. Moreover it is possible to aggregate the impacts to broader occupation categories and sectors to see the predicted impacts on two important aspects of long run employment trends: job polarization, and structural change of employment across sectors.

2.3.4.1 *Employment Share Growth*

Given the occupation-sector structure of employment in the model, the growth of occupational employment share can be expressed as follows:

$$\begin{aligned}
\frac{\partial s_{jt}}{\partial t} &= \frac{\partial L_{jt}}{\partial t}\frac{1}{L_{jt}}s_{jt} - \frac{\partial L_t}{\partial t}\frac{1}{L_t}s_{jt} \\
&= \left(\sum_{i=1}^{I}\frac{\partial \log L_{ijt}}{\partial t}s_{i|jt} - \sum_{i=1}^{I}s_{it}\left(\sum_{j=1}^{J}\frac{\partial \log L_{ijt}}{\partial t}s_{j|it}\right)\right)s_{jt}, \qquad (2.38)
\end{aligned}$$

where $s_{j(i)t} = \frac{L_{j(i)t}}{L_t}$ is the occupation j's (sector i's) employment share in year t; $s_{i|jt} = \frac{L_{ijt}}{L_{jt}}$ is share of industry i employment in a given occupation j and year t; $s_{j|it} = \frac{L_{ijt}}{L_{it}}$ is share of occupation j employment in a given industry i and year t.

Combining employment demand equation (2.34), price equation (2.30), and output demand equation (2.37), I express (2.38) in terms of estimated task impacts, elasticity parameters and task scores:[15]

15 I use the following approximation for the industry marginal cost equation:

$$\log(p_{it}) \approx \sum_{j=1}^{J} s_{j|it} \times \left(\frac{1}{\theta-1}\log\left(\phi_{ij}\right) + \log\left(w_t\right) - \log\left(A_{jt}\right)\right).$$

$$\begin{aligned}\frac{\partial s_{jt}}{\partial t} &= \left(\gamma_I ITI_j + \gamma_R RTI_j + \frac{(\theta-\epsilon)}{(1-\theta)}\left(\sum_{i=1}^{I} s_{i|jt}\left(\gamma_I ITI^I_{it} + \gamma_R RTI^I_{it}\right)\right)\right) s_{jt} \\ &- \left(\frac{1-\epsilon}{1-\theta}\left(\gamma_I ITI^A_t + \gamma_R RTI^A_t\right)\right) s_{jt}, \end{aligned} \tag{2.39}$$

where $\gamma_I = -(1-\theta)\gamma_{ITI}$, $\gamma_R = -(1-\theta)\gamma_{RTI}$ are estimated task impacts from labor demand equations; ITI^I_{it} and RTI^I_{it} are industry averages of task measures; ITI^A_t and RTI^A_t are economy averages of task measures.[16]

Equation (2.39) summarizes the effects of task-based technology on employment share growth. It can be inspected in three separate parts. First two summation elements on the right hand side (including occupation level task scores) correspond to direct effect of technology on labor demand. Higher ITI occupations increase their employment share since slower growing productivity in these jobs results in a higher demand due to less than unitary elasticity of substitution among tasks.[17]

The second group of summation involving industry mean task scores corresponds to the indirect demand effect on occupations. This effect ultimately depends on the difference between industry production task elasticity and consumption sector elasticity. Ceteris paribus, an occupation with higher average industry ITI increases its employment share if substitutability in production is higher than substitutability in consumption. The estimated elasticity parameters suggest that $\theta > \epsilon$, which implies that both direct and sector effects operate in the same way with regards to relative labor demand of an occupation. This channel effectively changes employment shares across occupations through variations in occupations' specialization in industries.

The last group in the summation (including economy-wide task scores) reflects the effect of relative demand change when aggregate task intensities change. The key in this effect is elasticity of substitution among industry output in consumption. If it is less than unitary, the occupation's employment demand falls with a higher economy-wide ITI score as a result of increased level of inefficiency. However this part plays no role in employment share changes across occupations since it is the same for all occupations.

16 Let Z denote the task variable. Industry task intensity is given by $Z^I_t = \sum_{j=1}^{J} s_{j|it} Z_j$, and aggregate task intensity is given by $Z^A_t = \sum_{i=1}^{I}\left[s_{it}\left(\sum_{j=1}^{J} s_{j|it} z_j\right)\right]$ for Z=ITI, RTI.

17 Throughout the text, the effects are exemplified through ITI. The results in the examples go in the opposite direction for higher RTI.

The setup also allows calculating the growth of industry employment share:

$$\frac{\partial s_{it}}{\partial t} = \frac{\partial L_{it}}{\partial t}\frac{1}{L_{it}}s_{it} - \frac{\partial L_t}{\partial t}\frac{1}{L_t}s_{it} = \left(\sum_{j=1}^{I}\frac{\partial \log L_{ijt}}{\partial t}s_{j|it} - \sum_{i=1}^{I}s_{it}\left(\sum_{j=1}^{J}\frac{\partial \log L_{ijt}}{\partial t}s_{j|it}\right)\right)s_{it}. \tag{2.40}$$

Using labor demand, output demand, and price equations (2.40) can be expressed as the following:

$$\frac{\partial s_{it}}{\partial t} = \frac{(1-\epsilon)}{(1-\theta)}\left(\gamma_I\left(ITI^I_{it} - ITI^A_t\right) + \gamma_R\left(RTI^I_{it} - RTI^A_t\right)\right)s_{it}. \tag{2.41}$$

The change of employment share depends on the elasticity of substitution in consumption, ϵ.[18] An industry with a relatively higher ITI score exhibits a relatively slower productivity growth. If $\epsilon < 1$ demand for that industry increases and consequently labor share grows. This is equivalent to the well-known labor reallocation result of structural transformation literature. Industry averages of task measures in this representation replace industry-specific TFP growth rates in the structural transformation models.

2.3.4.2 *Actual and Predicted Change in Employment Shares*

In this subsection I evaluate the model's performance in predicting occupational and sectoral employment shares. The model's prediction of occupational employment change between 1987 and 2014 is shown in Figure 2.1. The model performs quite well in mimicking changes in long run employment shares. The correlation coefficient between actual and total predicted is 0.89. The high correlation reflects matching signs as well as the magnitudes of changes by the model. To be more precise on the accuracy I calculate the weighted mean absolute percent error (WMAPE) as follows:

$$WMAPE^{occ} = 100 \times \sum_{j=1}^{J}\bar{s}_j\frac{\left|s^p_{j,2014} - s_{j,2014}\right|}{s_{j,2014}}, \tag{2.42}$$

where s_j is occupation's employment share, $\bar{s}$ stands for average employment share over 1987 and 2014 (rescaled to sum up to 1), and upper script p denotes the prediction. WMAPE measures how much (in percentage terms) the prediction deviates

18 Note that $(1-\theta)$ term cancels after multiplication with γ_I or γ_R.

from the actual on average. WMAPE calculated for occupation predictions is 13.45.[19] In other words, the task-based model on average is off by slightly below 14 percent.

Lighter and darker gray bars in Figure 2.1 illustrate the breakdown of predictions by the ITI and RTI measures, respectively. Bulk of the predicted contributions come from ITI, which is not surprising given the higher point estimate of ITI's impact on employment demand. The breakdown also suggests supportive evidence regarding the nature of task measures. For instance, clerical (office and administration support) jobs shrink in employment share by 3.02 percentage points. Exactly as the routinization hypothesis suggests, almost all of the decline is explained by RTI, while ITI suggests only a mild decline of 0.67 points. A notable example for counteracting task impacts is in laborers. Since those occupations are not so routinizable due to manual task requirements, employment is expected to grow relatively more in those occupations, which is consistent with RTI prediction indicated by the corresponding dark gray bar in the figure. However, the relatively impersonal nature of these jobs suggests that relative labor demand should fall for workers in this occupation group. In fact employment share of laborers contracts by 0.56 percentage points, which is predicted as 0.53 by the model thanks to ITI.

Figure 2.2 presents actual and predicted employment share changes for sectors. The predictions are based on equation (2.41). The overall fit of the model is again quite strong with a correlation coefficient of 0.91. This performance is remarkable given that most changes stem from a minority of sectors. I calculate the prediction error measure employed above, now for sectors as follows:

$$\mathrm{WMAPE}^{ind} = 100 \times \sum_{i=1}^{I} \bar{s}_i \frac{\left| s^p_{i,2014} - s_{i,2014} \right|}{s_{i,2014}}, \tag{2.43}$$

where where s_i is industry's employment share, $\bar{s}$ stands for average employment share over 1987 and 2014 (rescaled to sum up to 1), and upper script p denotes the prediction as above. WMAPE of sector predictions is calculated as 14.17, which implies that the task-based model's predictive performance in sectoral employment changes is similar to its capacity to explain occupational employment share changes.

The breakdown of predictions by task measures for sectors emphasizes again the fact that ITI and RTI counteract or complement each other depending on the context of production. Notable examples for the former are construction and retail trade

19 The same statistic can be computed for Table 4 of Goos, Manning, and Salomons (2014). Their task-based technical change model has WMAPE of 13.38 for European countries between for 1993-2010 period.

sectors. Construction sector is essentially non-routinizable and at the same time non-interpersonal. The effect of this on relative labor demand of construction industry is as expected: while predicted employment share rises 1.23 points due to RTI, it falls by 0.52 points as a result of low ITI score. Overall, there is a slight rise in employment share as predicted. For retail trade the story is reversed: a high routinizable content discouraging employment flows that is balanced by high interpersonal content that attracts employment.

There are also cases where both task channels act together such as manufacturing, and health and education sectors. These turn out to be the biggest players in employment shifts across sectors. Low ITI and high RTI content of manufacturing sector as well as high ITI and low RTI content of health and education seems to dominate together the employment share changes across sectors. What is more striking is the key role of ITI. It accounts for 92 percent of the fall in manufacturing, and 88 percent of health and education sector growth. Bulk of inter-sectoral reallocation of labor cannot be predicted if the impact of ITI is turned off.

2.3.4.3 *Implications for Job Polarization and Structural Change*

The disaggregated analysis above strongly suggests ITI as an important driver of occupational and industrial employment demand after taking the impact of RTI into account. Furthermore the contribution of ITI is significantly higher than RTI. In the following, I analyze the success of the model and relative impact of task measures on aggregated occupation and industry groups in order to have a clear understanding of both task dimensions in explaining job polarization and structural change.

Panel A of Table 2.7 aggregates the actual and predicted employment share changes to occupations grouped according to their place in the wage distribution following Table 2.1. The model performance in explaining aggregate employment shifts across occupation groups is notable: around 70 percent of high-pay and the middling, and 80 percent of low-pay occupation employment share change can be explained by the model.

The role of both task measures can be quantified by comparing the last three columns of predictions in the Table. The predicted portion explained by ITI is around 2/3. Together with the overall performance of the model, the implication is that most of job polarization can be explained by ITI while RTI plays a significant but limited role.

Panel B of Table 2.7 aggregates the employment change predictions for service producing sector following the classification in Table 2.2 as goods and services. The model can predict 90 percent of employment shift from goods to services. Interestingly, almost all of the prediction can be attributed to ITI leaving no significant role for RTI in explaining sectoral aggregate trends of employment growth.

2.3.4.4 *Addressing Issues on the Interpretation of Results*

The predictions discussed above can be interpreted that the task-based model of structural change provides a good description of the US labor market after late 1980s in respect of employment reallocation dynamics across occupations and sectors. In particular, measures of interpersonal-service intensity and routinizability jointly seem to form the key task aspects of structural changes of employment. On the other hand, one needs to be careful on the task measures before accepting their individual predictive capacity at face value.

ROBUSTNESS BY VARIABLE CHOICE: The most important potential concern is whether the individual predictions are sensitive to the choice of task variables. In order to have an idea of the robustness of the results, I construct alternative variables for measuring ITI and RTI.

For ITI, I use "deal with external customers" variable from O*NET database. It is one of the variables that make the original ITI index and it is conceptually sufficient for capturing the key aspect. On the other hand, the literature seems to reach a consensus in using RTI as a reliable measure of routine task intensity. Therefore, it is hard to argue here that an alternative measure is as a good proxy for routinization as the composite RTI variable constructed from Autor, Levy, and Murnane (2003)'s original task aspects. As the best alternative, I generate the O*NET version of RTI using Acemoglu and Autor (2011)'s proposed alternatives to original DOT variables.

Table 2.A.1 compares the predictions obtained when alternative variables are used in the estimation of the model.[20] As shown at Panel A, the overall performance of the model in predicting job polarization changes as the alternative variables predict top occupations better at the expense of bottom jobs while the contraction in middle wage occupations is predicted similarly by both the original original and the alternative set

20 Note that in terms of predictive capacity of the model both the point estimates from the conditional labor demand estimation and the distribution of task scores across occupations and sectors are important.

of task variables. Panel B of the table reports that the alternative variables overshoot the growth of service sector employment share by around 2.75 percentage points, which is about 30 percent of the actual.[21]

Observing such changes in the overall performance of the model is not surprising given that original variables are more carefully constructed for the purpose of this study and the routinization framework. What is more important for the current discussion is the key result of this paper that bulk of the predictive capacity of the model comes from interpersonal-service tasks. Comparing individual predictions to total, Table 2.A.1 suggests that ITI measure in the alternative model accounts for 57, 61 and 102 percent of the total predicted change for the top, middle, and bottom occupations, respectively. Similarly, ITI continues to dominate the predictions for service sector growth as almost all of the predicted changes in service employment share comes from interpersonal-service task variable.

INTERPRETATION OF ITI WITH RESPECT TO ROUTINIZATION: The second concern could be the following: the result that interpersonal-service tasks are the most important dimension of task demand changes does not necessarily mean that overall routinization is less effective, since ITI can potentially capture unmeasured elements of routinizability. This concern is worth addressing here because although a valuable measure of routinizability, RTI is still an imperfect one. If this concern is right, perhaps interpersonal-service tasks complement the routinization view. In particular, ITI augments the existing framework in adding a new element to the non-routine tasks. In fact this approach is taken by some papers in the literature (Goos, Manning, and Salomons, 2009; Lee and Shin, 2017). Moreover, the bottom wage occupations are mostly characterized by personal services, which have high interpersonal-service content and often are the typical examples of non-routine manual tasks in the routinization literature (e.g., Autor and Dorn, 2013; Goos, Manning, and Salomons, 2014). However, interpersonal-service tasks are not addressed formally in the original routinization framework. It is true that many interpersonal-service intensive personal service jobs have also above-average scores in non-routine manual tasks, however among high ITI tasks there are routine and abstract intensive jobs too.

21 The correlation coefficient between actual and predicted occupational employment share changes is 0.72 and the WMAPE for occupation employment share predictions is 19.93. The correlation coefficient between actual and predicted sectoral employment share changes is 0.91 and the WMAPE for occupation employment share predictions is 15.61.

Whether ITI is part of the routinization framework is extensively studied in Chapter 1 of this thesis. The Chapter argues that ITI does not fit into the existing routinization framework since (i) it is different than non-routine cognitive interactive tasks; (ii) it is different than non-routine manual tasks; (iii) it is not negatively associated to direct ICT intensification measures as one expects according to the routinization hypothesis. Therefore the existing evidence does not support a clear role for interpersonal-service tasks within the routinization view. The estimated impact of ITI on employment reallocation largely reflects the technical change apart from computerization.

ALTERNATIVE HYPOTHESES: Finally, I evaluate other potential drivers of task demand in the literature, namely offshoring and demand shifts due to non-homothetic preferences. There is growing evidence in the literature on the poor performance of offshorability in reallocation of employment (Autor and Dorn, 2013; Goos, Manning, and Salomons, 2014; Lee and Shin, 2017). In Figure 2.A.1 and 2.A.2 I show the predictions and actual changes when I model technology growth as a linear function of offshorability.[22] The offshorability variable is from Autor and Dorn (2013). The figures clearly confirm with the dataset of this paper that offshorability does not seem as a significant task-based channel in changing occupational and sectoral structure.

The recent task literature also lacks empirical support for a significant impact of non-homothetic preferences on labor demand.[23] Preferences are conceptually argued to impact both sector (e.g., Kongsamut, Rebelo, and Xie, 2001) and occupation demand (e.g., Manning, 2004). The sector-time fixed effects discussed in section 3.3 can be argued to partially account for the impact of non-homothetic preferences. To the extent that the household directly consumes only final goods and services of sectors as currently modeled in the paper, sector-time fixed effect estimation results suggest that sector-based non-homotheticities perhaps do not play a big impact in the changing task demand. However, there are cases where occupation-specific demand growth of such type is not fully absorbed by sectors. For instance, customer service jobs are demanded by customers regardless of the sector and consumers might be willing to disproportionately get more of them as income grows. This is a more relevant concern for ITI as the preference explanation is based on a growing demand for services.

22 The observationally equal case is having capital in the model and assuming faster declines in capital prices in more offshorable tasks (Goos, Manning, and Salomons, 2014).

23 Non-homotheticity is found more useful in the structural change literature. However the key role of preferences is in explaining the behavior of real consumption and expenditure shares (Herrendorf, Rogerson, and Valentinyi, 2014), which is outside the scope of the current analysis.

Therefore, the estimated impact of ITI can be affected by preferences, which is not in line with the technology perspective of this paper. Although the current specification does not allow a direct control for this possibility, Figure 2.A.3 provides indirect evidence. The idea is to compare the predictive performance of ITI for service intensive occupations against non-service ones, as non-service occupations are a lot less likely to grow due to income effects favoring services. If the preference channel is a major concern, then we should observe that the model has a good fit among service intensive jobs and a bad one within non-service occupations. The figure evidently shows that ITI does not have a superior fit for service occupations. If anything, predictions for non-service occupations seem to have a better fit, suggesting that income effects are not driving the model's success.

2.4 Conclusion

In this paper I estimate an occupation-specific technical change model for the US economy. The key assumption of the model is that the technical change is biased against interpersonal-service tasks and in favor of routinizable ones. Consistent with the model, these two task aspects play a substantial role in the reallocation of employment across occupations and sectors. Moreover the task-based model can account for a substantial part of the changing structure of employment in the last 3 decades.

This paper estimates a dominating impact for interpersonal-service tasks in explaining both job polarization and the growth of service sector employment in the US. On the other hand, routinization has a substantial impact on polarization of employment, but arguably more limited than the previous task-based literature expects. Furthermore, I observe that the employment impact of routine-biased technical change largely took place during 1990s, while reallocation of employment into interpersonal-service intensive occupations follows a more balanced course throughout the sample period.

As a result of continuously rising relative demand, the service economy has become the most important part of the labor markets. Therefore, the research on the changing structure of employment across different segments in the economy demands a better knowledge of within-sector forces of resource reallocation. By illustrating the success of the task-based model to explain sector as well as occupation employment dynamics, and emphasizing the role of customer oriented interactions I hope this paper contributes in this direction.

2.A Tables

Table 2.1: Occupations, Task Scores and Change in Employment

	A. Task Scores		B. Employment Share		
	ITI	RTI	1987	2014	Change
High-Wage Occupations	**0.26**	**-0.38**	**37.28**	**45.52**	**8.24**
Legal	0.86	2.00	0.71	0.92	0.21
Computer, math sciences and eng.	-1.12	-0.97	2.79	3.34	0.55
Managers	0.60	-0.92	11.00	13.00	2.00
Life, physical and social sciences	-0.98	-0.17	0.64	0.68	0.04
Healthcare practitioners and techn.	1.59	-0.48	4.04	5.91	1.88
Technical except health	-1.33	-0.12	2.10	2.85	0.75
Business, finance, and management rel.	0.10	0.70	9.78	10.38	0.60
Education, training, library	0.46	-1.64	4.76	6.61	1.85
Arts, design, sports and media	-0.51	0.28	1.46	1.83	0.36
Middle-Wage Occupations	**-0.40**	**0.83**	**52.64**	**41.39**	**-11.25**
Mechanics and repairers	-0.34	-0.24	4.82	3.59	-1.24
Precision production	-1.36	0.89	3.80	2.42	-1.39
Extraction and construction trades	-0.32	-0.83	4.64	3.82	-0.82
Community and social service	2.15	0.09	0.91	1.29	0.38
Drivers and mobile plant operators	0.31	-1.33	4.04	4.14	0.10
Office and administrative support	-0.37	2.49	15.32	12.31	-3.02
Sales and related	0.83	0.80	6.58	5.75	-0.82
Machine operators and assemblers	-1.56	0.81	8.41	4.53	-3.88
Laborers	-0.70	0.04	4.10	3.54	-0.56
Low-Wage Occupations	**0.40**	**-0.18**	**10.09**	**13.09**	**3.01**
Personal services	0.19	-0.13	8.46	10.10	1.63
Healthcare support	1.52	-0.47	1.62	3.00	1.37

Notes: Occupations are ordered according to CPS mean wages over all years from 1987 to 2014. Employment is annual hours worked. Employment shares are multiplied by 100.

Table 2.2: Industries, Mean Task Scores and Change in Employment

	A. Task Scores		B. Employment Share		
	ITI	RTI	1987	2014	Change
Goods Sector	**-0.54**	**0.08**	**29.86**	**21.34**	**-8.53**
Mining	-0.40	-0.15	0.87	1.06	0.18
Utilities	-0.41	0.20	1.65	1.42	-0.23
Construction	-0.21	-0.47	6.56	6.82	0.26
Manufacturing	-0.69	0.31	20.78	12.04	-8.74
Service Sector	**0.20**	**0.18**	**70.13**	**78.67**	**8.53**
Wholesale trade	0.12	0.49	5.00	3.03	-1.97
Retail trade	0.17	0.41	16.17	16.80	0.63
Transportation and warehousing	-0.03	0.09	4.97	5.35	0.38
Information	-0.38	0.20	4.64	4.99	0.34
Finance, ins., real est., rental, leasing	0.00	0.79	7.77	8.19	0.42
Professional and business services	-0.07	0.42	6.88	9.17	2.29
Education, health care, social assistance	0.63	-0.32	17.54	23.75	6.22
Arts, ent., rec., accom., and food services	0.15	0.02	1.95	2.68	0.72
Other services, except government	0.15	0.08	5.21	4.71	-0.50

Notes: Industries are according to NAICS classification. Employment is annual hours worked. Employment shares are multiplied by 100. Industry task scores are industry averages across occupations using labor supply weights in the pooled sample.

Table 2.3: Labor Demand Estimation

(Dependent Variable: Log Annual Hours Worked, 1987-2014)

	(1)	(2)	(3)	(4)	(5)
Time Trend ×					
ITI	0.69***		0.64***	0.68***	0.65***
	(0.21)		(0.21)	(0.22)	(0.21)
RTI		-0.42***	-0.35***	-0.34**	-0.35***
		(0.14)	(0.13)	(0.14)	(0.13)
Industry output	1	1	1	1	0.86***
					(0.11)
Industry marginal cost	0.85***	0.86***	0.86***		0.77***
	(0.08)	(0.08)	(0.08)		(0.09)
Industry value-added price index				0.75***	
				(0.09)	
Observations	6,400	6,400	6,400	6,400	6,400
R^2					0.95

Notes: Table reports estimated coefficients from different specifications of labor demand in columns. Observation unit is industry-occupation. Estimates of interaction of time trend with task measures are multiplied by 100. Industry output, marginal cost, and value-added price index is in logs. (1) to (4) are estimated as constrained regressions. All columns contain industry-occupation and year dummies. Standard errors clustered by occupation-industry are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2.4: Change in Labor Demand: Occupation-Specific and Sector-Specific Growth

(Dependent Variable: Log Annual Hours Worked, 1987-2014)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Time Trend ×										
ITI	0.66***		0.62***		0.69***		0.64***	0.66***		0.62***
	(0.20)		(0.20)		(0.21)		(0.21)	(0.19)		(0.19)
RTI		-0.42***	-0.35***			-0.42***	-0.35***		-0.41***	-0.34***
		(0.13)	(0.13)			(0.13)	(0.13)		(0.13)	(0.12)
Service Sector Dummy				0.26	0.19	0.25	0.18			
				(0.41)	(0.38)	(0.40)	(0.38)			
Sector Dummies (Detailed)	-	-	-	-	-	-	-	✓	✓	✓
Industry-Year Fixed Effects	✓	✓	✓	-	-	-	-	-	-	-
Observations	6,400	6,400	6,400	6,400	6,400	6,400	6,400	6,400	6,400	6,400
R^2	0.96	0.96	0.96	0.95	0.95	0.95	0.95	0.95	0.95	0.95

Notes: Table reports estimated coefficients from different specifications of labor demand in columns. Observation unit is industry-occupation. Estimates of interaction of time trend with task measures and sector dummies are multiplied by 100. (1) to (3) include industry-occupation dummies. (4) to (10) include year and industry-occupation dummies, and industry output and marginal cost variables. Industry output and marginal cost are in logs. Standard errors clustered by occupation-industry are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2.5: Change in Labor Demand and Tasks: Subperiods

(Dependent Variable: Log Annual Hours Worked, 1987-2014)

	1987-2000			2001-2014		
	(1)	(2)	(3)	(4)	(5)	(6)
ITI	0.84**		0.72**	0.95***		0.96***
	(0.36)		(0.35)	(0.28)		(0.28)
RTI		-0.99***	-0.91***		-0.01	0.10
		(0.21)	(0.21)		(0.20)	(0.19)
Observations	3139	3139	3139	3261	3261	3261
R^2	0.97	0.97	0.97	0.96	0.96	0.96

Notes: The table reports estimated coefficients of task measures multiplied by time trend in different labor demand specifications in columns. Reported coefficients are multiplied by 100. Observation unit is industry-occupation. All regressions contain industry-occupation and industry-year dummies. Standard errors clustered by occupation-industry are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2.6: Industry Demand Estimation

(Dependent Variable: Log Output, Value Added)

	1947-2014	1987-2014	
	(1)	(2)	(3)
Log Relative Price	-0.52***	-0.45***	
	(0.04)	(0.05)	
Log Relative Marginal Cost			-0.48***
			(0.03)
Observations	884	364	364
R^2	0.96	0.99	0.99

Notes: The table reports estimated coefficients in different specifications of industry output demand in columns. All regressions contain industry and year dummies. Output and relative price and cost data are from BEA. Robust standard errors are in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2.7: Trends in Employment Demand: Actual vs Model
(100 $\times$ Employment Share Change, 1987-2014)

	Actual	Predicted		
A. Job Polarization	Total	Total	ITI	RTI
High-Wage	8.24	5.72	3.41	2.31
Middle-Wage	-11.25	-8.16	-5.19	-2.96
Low-Wage	3.01	2.42	1.77	0.65
B. Structural Change				
Service Sector	8.53	7.72	8.02	-0.31

Notes: Occupation groups and service sector definition follow Table 2.1 and Table 2.2. Actual refers to the long change in employment share observed in the data. Column Total reports predictions as described in Figure 2.1 notes (for Panel A) and 2.2 notes (for Panel B). Last two columns report individual predictions by the respective task measure when the effect of the other on labor demand is held constant.

Table 2.A.1: Predictions with Alternative Measures: Actual vs Model

(100 × Employment Share Change, 1987-2014)

	Actual	Predicted		
A. Job Polarization	Total	Total	ITI*	RTI*
High-Pay	8.24	7.74	4.41	3.33
Middle-Pay	-11.25	-8.50	-5.18	-3.32
Low-Pay	3.01	0.76	0.77	-0.01
B. Structural Change				
Service Sector	8.53	11.27	10.37	0.90

Notes: The predictions use task coefficients of alternative measures of ITI (ITI* in the table) and RTI (RTI* in the table) as defined in the text. For all other details see Figure 2.1 notes (for Panel A) and 2.2 notes (for Panel B). Last two columns report individual predictions by the respective task measure when the effect of the other on labor demand is held constant.

2.B Figures

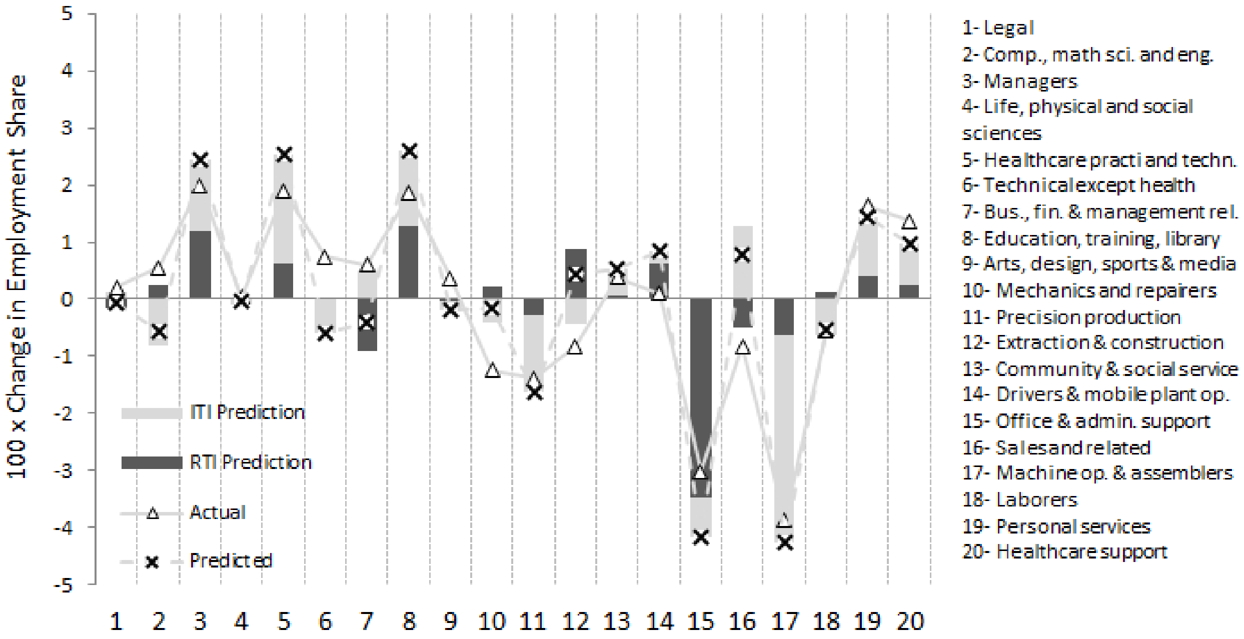

Figure 2.1: Occupation Employment Share Changes: Actual vs. Predictions

Notes: The figure shows the actual and predicted occupation employment share changes, and breakdown of predictions by ITI and RTI. Predictions are based on equation 2.39. Parameter values are from column (3) of Table 2.3 for tasks' impact on labor demand growth; the simple average of the coefficient of industry marginal cost in column (3) and industry value-added price index in column (4) of Table 2.3 for task input elasticity in sector production; and the simple average of the coefficient of relative industry marginal cost in column (2) and relative industry value-added price index in column (3) of Table 2.6 for output elasticity in consumption. Individual predictions by each task measure are computed such that the effect of the other on labor demand is held constant.

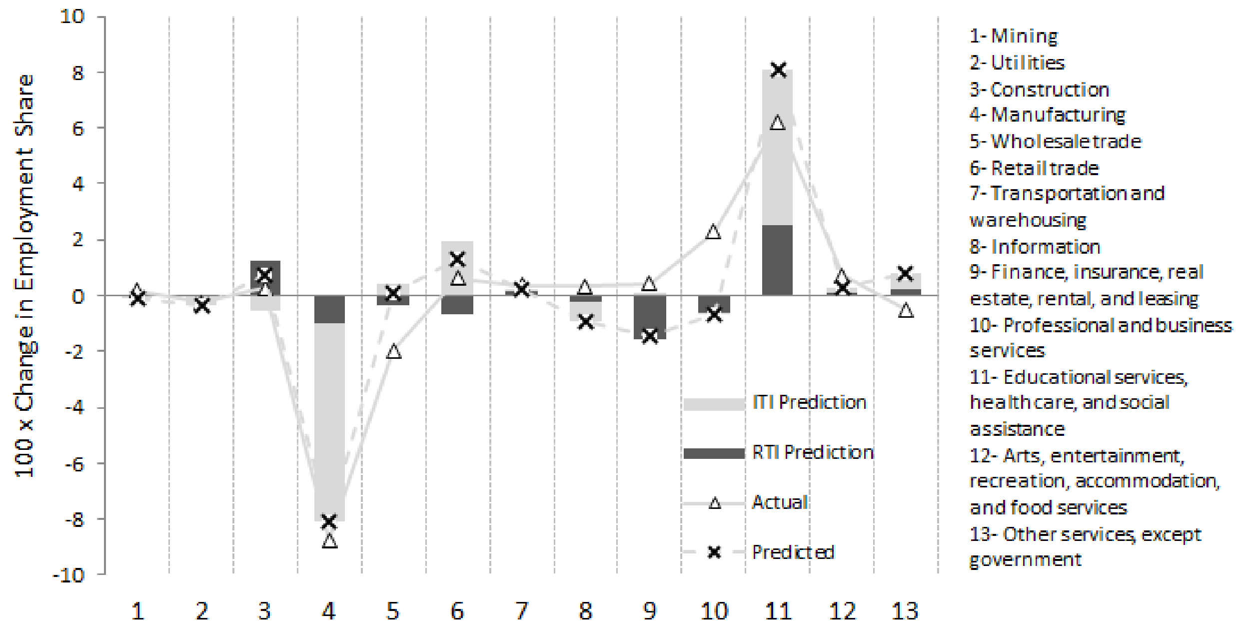

Figure 2.2: Sector Employment Share Changes: Actual vs. Predictions

Notes: The figure shows the actual and predicted occupation employment share changes, and breakdown of predictions by ITI and RTI. Predictions are based on equation 2.41. Parameter values are from column (3) of Table 2.3 for tasks' impact on labor demand growth; the simple average of the coefficient of industry marginal cost in column (3) and industry value-added price index in column (4) of Table 2.3 for task input elasticity in sector production; and the simple average of the coefficient of relative industry marginal cost in column (2) and relative industry value-added price index in column (3) of Table 2.6 for output elasticity in consumption. Individual predictions by each task measure are computed such that the effect of the other on labor demand is held constant.

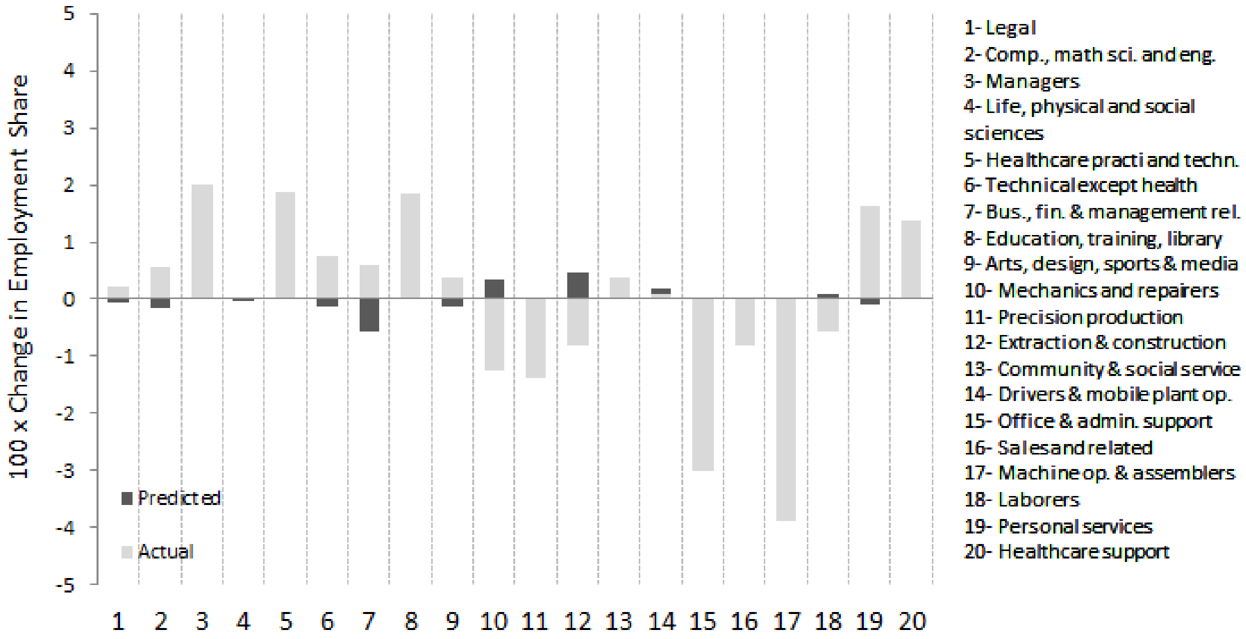

Figure 2.A.1: Performance of Offshorability Measure: Actual vs. Predicted Changes in Occupation Employment Shares

Notes: The figure shows the actual and predicted occupation employment share changes from the estimation of the task model of offshorability which provides the coefficient of the offshorability measure. For other details of the computation see Figure 2.1 notes.

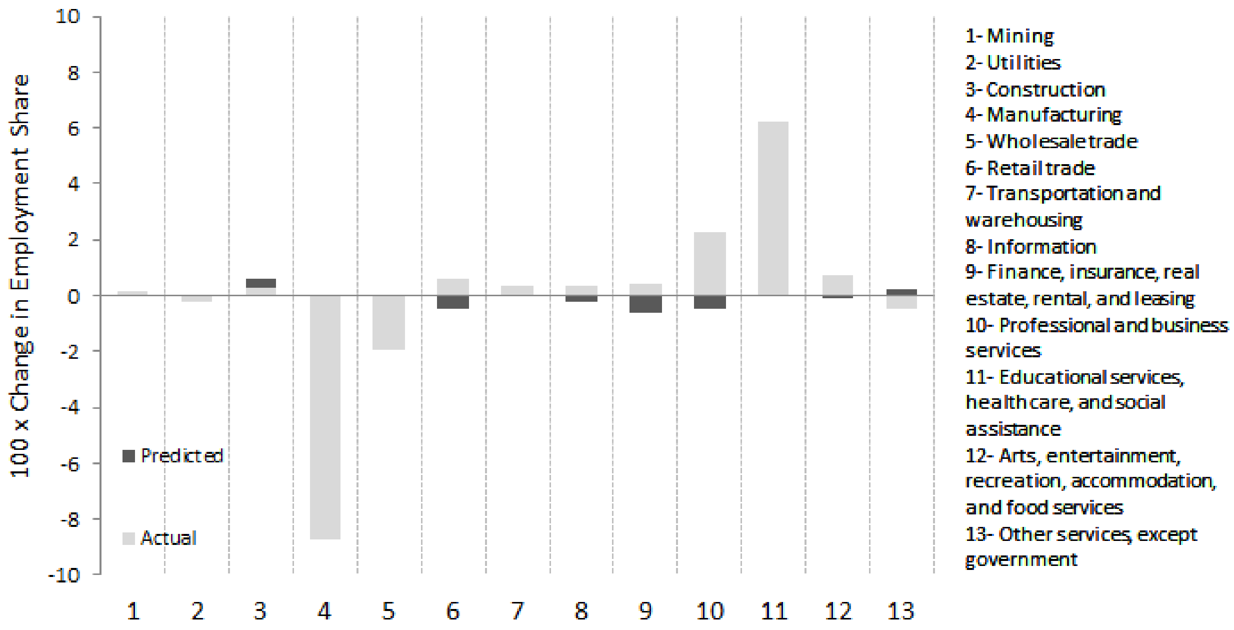

Figure 2.A.2: Performance of Offshorability Measure: Actual vs. Predicted Changes in Sector Employment Shares

Notes: The figure shows the actual and predicted occupation employment share changes from the estimation of the task model of offshorability which provides the coefficient of the offshorability measure. For other details of the computation see Figure 2.2 notes.

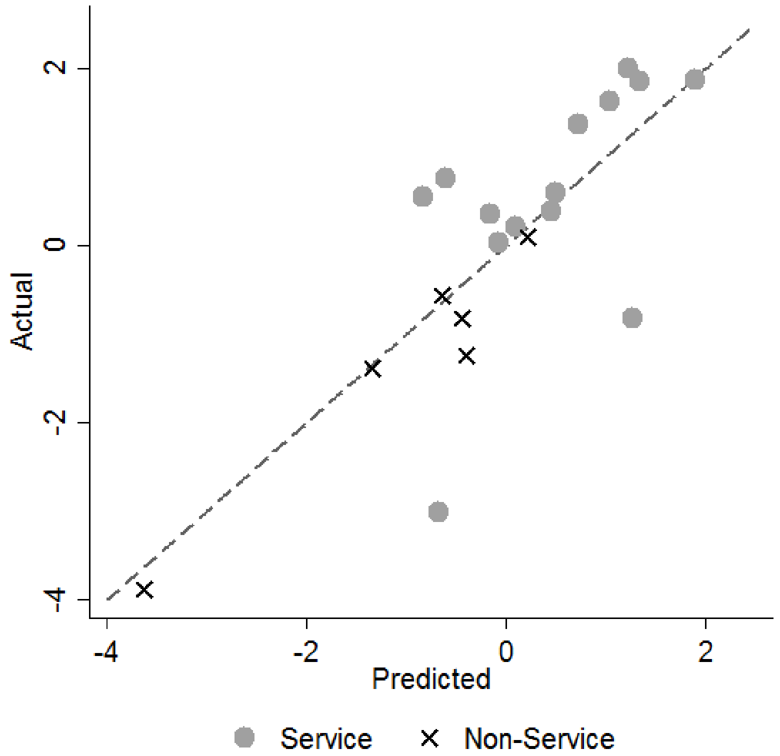

Figure 2.A.3: ITI and Employment Growth: Actual vs. Predicted Changes Employment Shares by Service Intensity of Occupations

Notes: The figure plots the actual vs. predicted occupation employment share changes from the estimation of the task model. The predictions are ITI's individual contributions as in Figure 2.1. The service occupation definition is adopted from Duernecker and Herrendorf (2017). Non-service occupations are mechanics and repairers; extraction and construction workers; precision production workers; machine operators and assemblers; drivers and mobile plant operators; laborers in transport, manufacturing, construction and extraction. All other occupations belong to service intensive occupations.

2.C Data Appendix

I describe the details of CPS sample used in this study here. CPS data refer to CPS March extracts. The sample includes workers of age 16-64, employed workers, excluding armed forces, self-employed, and unpaid family workers who reported positive wage income. Employment of an occupation is total annual hours worked computed as usual weekly hours times weeks worked variables. Labor supply weights are calculated as annual hours times population weights.

Chapter 3

SKILL-BIASED TECHNICAL CHANGE AND LABOR MARKET POLARIZATION: THE ROLE OF SKILL HETEROGENEITY WITHIN OCCUPATIONS

I document that employment share change and wage growth of occupations tend to increase monotonically with various measures of skill intensity since 1980 in the US, in contrast to the existing interpretation of labor market polarization along occupational wages. The observation is not particularly driven by a specific decade, gender, age group, or occupation classification. The evidence suggests that polarization by wages does not imply polarization of skills that have cross-occupation comparability. Skill-biased and polarizing occupation demand coexist as a result of the weak connection of wage and observable skill structure particularly among the low-wage jobs in the 1980. The empirical findings of the chapter can be reconciled in an extended version of the canonical skill-biased technical change model which incorporates many occupations and within-occupation heterogeneity of skill types.

3.1 Introduction

The task-based view in labor economics has had a profound impact on the way economists perceive inequalities in the labor market. Perhaps, this impact is most notable in our understanding of skill-biased technical change (henceforth SBTC), which has been a cornerstone in the wage inequality literature.[1] The canonical model of SBTC typically assumes skilled and unskilled workers in the economy where tasks and skills are implicitly equivalent (Katz and Murphy, 1992). The task perspective emphasizes the conceptual difference of work activities (tasks) from the set of productive worker capabilities (skills) (Acemoglu and Autor, 2011), and the practical importance of occupations as the unit of empirical analysis (Firpo, Fortin, and Lemieux, 2011).

One implication of the task perspective in the literature has been the development of a nuanced view on technical change, where recent advances in computer technology affect abstract, routine, and manual tasks in different ways (Autor, Levy, and Murnane, 2003). The resulting emphasis on occupations revealed an important aspect of labor market inequalities that the canonical model could not predict, namely labor market polarization referring to slower growth in employment and wages in middle-wage jobs relative to others located at the tails of the wage distribution.[2] The literature often interprets polarization in terms of skills, as the manifestation of non-monotonic changes in the demand for skills as opposed to the monotonicity implied by the canonical model (see, e.g., Acemoglu and Autor, 2011; Autor and Dorn, 2013; Autor, Katz, and Kearney, 2006; Goos and Manning, 2007)

Untangling tasks from skills has proved itself as an empirically remarkable improvement over the canonical model, however both approaches still share a common assumption that strictly isolates skill-types in the performance of a given task. In other words, a task can only be performed by a single type of worker, either absolutely (as

1 See Goldin and Katz (2008) both for the empirical evidence on how the simple demand and supply framework of SBTC, which is referred to as the canonical model in Acemoglu and Autor (2011), can successfully help to understand the evolution of the labor market inequalities, and for a review of the literature on the SBTC.

2 Polarization is shown to be a pervasive phenomenon both in the US (Autor, Katz, and Kearney, 2008; Autor and Dorn, 2013; Autor, Katz, and Kearney, 2006), the UK (Goos and Manning, 2007), and many other advanced economies (Goos, Manning, and Salomons, 2009, 2014). Barány and Siegel (2017) argue that polarization starts as early as the 1950s in the US. Polarization has been the most influential illustration of how the canonical SBTC model fails to explain trends of inequality at occupation level (e.g., Autor, Katz, and Kearney, 2008; Autor, Katz, and Kearney, 2006; Goos and Manning, 2007). See Acemoglu and Autor (2011) and Acemoglu and Autor (2012) for other evidence which cannot be explained within the canonical model.

in the canonical model) or conditional on the state of technology (as in task-based models).[3] The aim of this paper is to relax this assumption and explore the role of occupational skill heterogeneity by providing a characterization of the evolution of inequalities with respect to differences in observable skill intensities across tasks.

The motivation for this study can be summarized in Figure 3.1, which plots smoothed shares of skill groups in 1980 occupational employment by occupations' wage percentile ranking. The education shares of employment imply substantial heterogeneity within occupations when ranked by wages. All types of skills are found in significant shares in employment throughout the distribution with varying weights. Furthermore, from the lens of education intensities it does not seem realistic to characterize occupations throughout the wage distribution as high-, low- and middle-skilled. While the high school dropouts tend to have a higher share in employment towards the lower tail of the distribution, this group appears nowhere as the dominating skill component of jobs. Similarly, both high school graduates and workers with some college education, who can be considered as the middle-skill workers, do not show a drastic tendency to grow in the middle of the wage distribution compared to the lower tail.[4] Instead, there is a clear disconnect between education and wages for occupations below the median wage.

Figure 3.1 raises two important questions regarding the skill-based interpretation of the cross-occupation inequality trends. Can labor market polarization be consistently confirmed by skill measures other than wages? Are there any implications of within-occupation heterogeneity of skill types in the reallocation of employment across tasks and in the evolution of wages? While answering these questions this paper contributes to the existing literature in the following aspects.

The first contribution of the paper is to document that polarization observation in the long run is only limited to wage ranking of occupations in a set of available skill measures. When the skill measure used is the share of college workers in employment, which is the relevant variable for assessing the skill content according to SBTC hypothesis, occupational employment and wage changes follow a monotonic path proportional to occupational skills rather than a u-shape. Other education-based

3 The existing task literature is well aware of skill heterogeneity within occupations (e.g., Goos and Manning, 2007). However, this is not reflected in the task-based models and explanations of inequality trends.

4 There is no consensus in the task literature on the educational content of the middle-skill type. Acemoglu and Autor (2011) include both high-school graduates and workers with some college education while Autor and Dorn (2013) exclude the latter group of workers.

variables as well as measures of trainability and ability also suggest that employment and wage growth of occupations are proportional to skill intensity. The observed monotonic growth is broadly robust to the choice of occupation classification, prevails within each decade from 1980 to 2010, and holds within the labor market for each gender and age group.

The second contribution is a set of empirical observations that speak to the determinants of the documented contrasting patterns of inequality by wage and skill rankings and explore the connection between the structure of occupational wages and skills in 1980. In order to understand what stands behind the observed mismatch between polarization and monotonic changes in task demand, I extend the evidence leading to Figure 3.1. Using a broad set of skill measures, I argue that occupational mean wage is not a good proxy of worker skills for jobs at the lower half of the wage distribution. In addition, occupational wages reflect other occupation-specific attributes such as how demanding the job is in terms of working time and cognitive processing capacity, and the level of exposure to hazardous conditions, better than acquired skills or education for the low-wage jobs in 1980. The data also reveals that distribution of skills by wages in broader occupation groups is beyond the stylized three-skill view that matches specific occupation groups to certain skill types. Remarkably, the so-called low-skill service occupations on average exhibit higher skills than many of the so-called middle-skill occupations along the wage distribution. Finally, I bring evidence showing that college workers are a significant part of lower skilled occupations and both college and non-college workers played a substantial role in the relative employment growth of bottom and top wage occupation groups.

Third contribution is to reconcile the first two set of findings. I present a simple extension of the canonical SBTC model to many occupations, which nests the skill premium equation of Katz and Murphy (1992), and show that the observed monotonic employment and mean wage growth is consistent with it. Furthermore, if the occupational wage structure does not solely depend on the mean observable skill intensity but other task-based attributes such as occupation-specific differences in preferences, the model is also qualitatively capable of explaining labor market polarization along wage distribution jointly with monotonic changes by skills.[5]

5 I illustrate a framework based on compensating differentials across occupations. Same qualitative results can also be motivated by a Roy-type occupation-specific productivity that is heterogeneously distributed across workers (see, e.g. Barány and Siegel, 2017). My modeling choice for compensating differentials is due to my observation that occupational wage structure can be better predicted by task attributes that are potentially associated with disutility from work (such as required hours of work for the job)

The most important element of the model is that low-skill and high-skill workers, though in different proportions, jointly contribute to the production of tasks in all occupations. The key mechanism to generate the labor demand forces is given by variation in SBTC-driven labor productivity growth across occupations and differences in the share of college to non-college workers. Hence, occupation-specific productivity growth drives labor reallocation as in models of structural change.[6] Having multiple skill types to perform the same task is also the distinctive feature of the model compared to the existing models of SBTC. While the model successfully rationalizes the monotonic occupation growth patterns, a simple predictive exercise on major occupation groups suggests that predictions of employment share change and wage growth by skill intensity differences across occupations are also compatible with polarization by wages.

I suggest that a labor market view where technical change favors not only high-skill workers but also the occupations employing better skilled ones is an acceptable characterization of the reality. This perspective is also partially compatible with non-monotonic evolution of employment demand along occupational wages. I put forward an additional modification to the task approach by stressing the importance of within-occupation heterogeneity of skills for the dynamics of inequality.

This paper is located within the broad SBTC literature that aims to characterize labor market inequalities in terms of skills. The approach held here can be seen as a combination of the canonical SBTC model with the task-based models. I extend the canonical model to include occupations. On the other hand, this paper diverges from the existing task-based SBTC literature by relaxing the strict assignment of skills to tasks conditional on the state of technology.[7] SBTC at occupation level introduces an alternative channel of task demand shift. Therefore this paper complements the literature on task level sources of disaggregate inequality trends such as routine-biased

compared to three task elements of routinization hypothesis. See Bryson and MacKerron (2016) for evidence on the negative impact of working on happiness. Authors also document that the negative impact is significantly lower for individuals at lower income levels. Bryson, Barth, and Dale-Olsen (2012) presents direct evidence on the negative association of wages with worker wellbeing.

6 The structural change literature suggests that sector-specific differential growth in TFP is a source of labor reallocation (e.g., Ngai and Pissarides, 2007). The same idea can also be applied in the context of occupational structural change (e.g., Autor, Katz, and Kearney, 2008; Goos, Manning, and Salomons, 2014).

7 Acemoglu and Autor (2011) develop a model where three skill types are assigned to a continuum of tasks such that the assignment is subject to change following changes in skill-specific technologies. Autor, Katz, and Kearney (2006) and Autor and Dorn (2013) assume that college workers can only perform abstract tasks. Non-college workers can move between routine and manual tasks. In both type of models, conditional on the technology parameters, there is a one-to-one mapping from skill types to tasks.

technical change (e.g., Autor and Dorn, 2013; Autor, Levy, and Murnane, 2003; Goos, Manning, and Salomons, 2014), offshoring (e.g., Blinder, 2009; Blinder and Krueger, 2013; Jensen and Kletzer, 2010), institutional changes (e.g., Lemieux, 2008), and structural change (Barány and Siegel, 2017; Duernecker and Herrendorf, 2017).

On the other hand, this paper contrasts with the existing skill-based interpretation of labor market polarization, which argues that the observed polarization patterns imply polarization of skills in the labor market.[8] The results of this study suggest that the existing occupational polarization can at most be interpreted as polarization of the market value of occupation-specific skills in the face of evidence on monotonic occupation growth by skills that are comparable across occupations. Therefore my results indirectly support the use of models on polarization that employ task-specific skills (e.g., Firpo, Fortin, and Lemieux, 2011).[9]

The paper is closest to Cerina, Moro, and Rendall (2017) outside the task-based literature. Cerina, Moro, and Rendall (2017) develop a multisector model with worker heterogeneity in gender, education and sector-specific ability, where the driver of polarization is SBTC as in this paper. The intuition of the mechanism in their model is that increasing skill premium attracts more women from home production into high-skill service sector, and consequently the demand for services that are substitutable to those produced at home, which are mostly located at the bottom of wage distribution, increases. Two papers differ mainly in terms of the basis of production in the economy. While they have a sector-based model, my study solely focuses on employment and skills in occupations and abstracts from sectors.[10]

The rest of the paper is structured as follows. Section 3.2 introduces the data used in this paper. Section 3.3 documents the empirical observations. In particular, first I show the evolution of occupational employment and wages throughout the skill distribution followed by analyses for robustness and validity of the observation. Then I discuss the evidence on the distribution of skills along the wage structure and across occupation groups using several alternative skill measures and on the role of college workers in job polarization. Section 3.4 introduces the theoretical framework that

8 The discussion in this paper is limited to skill-based interpretation of polarization. Papers that directly test the effect of intensification of recent technologies on the demand for different skill types (e.g., Michaels, Natraj, and Van Reenen, 2014) remain outside the scope of this paper.

9 Barány and Siegel (2017) and Cerina, Moro, and Rendall (2017) also develop Roy-type models to explain job polarization in the US. Although these models apply to sectors the idea can be easily adopted to task-specific abilities.

10 A further difference is in terms of methodology. Cerina, Moro, and Rendall (2017) calibrate their model to explore the implications of the model whereas I follow an essentially descriptive approach here.

rationalizes the observations made in previous sections. Section 3.5 concludes the paper.

3.2 Data

The main unit of analysis throughout this paper is detailed occupations. I classify occupations following Dorn (2009) who develops a consistent and balanced set of occupation codes that allow comparability across 1980, 1990, 2000 Census, and 2005 American Community Survey (ACS). For occupations in 2010 ACS I first transform 2010 *occ* codes to ACS 2005 *occ* equivalents, and then merge according to the crosswalk by Dorn (2009). Excluding farming and fishing occupations, I end up with a balanced panel of 322 occupations. In some parts of the empirical analyses I also employ six broader (major) occupation groups constructed from the detailed occupations following Autor and Dorn (2013).

I use 1980, 1990, 2000 IPUMS Census, and 2010 ACS data for calculating occupational employment shares, real wages and skill variables based on formal schooling. The measure of employment is annual hours worked which is aggregated to occupations using Census weights. Wages used are hourly and computed as annual wage income divided by annual hours. Real wages are calculated by an adjustment of nominal hourly wages by Personal Consumption Expenditure (PCE) Index. I have two main skill variables generated from Census data, mean years of education and share of college workers. College worker unless stated otherwise is defined by having any level of education above high school. In the calculation of all occupational averages observations are weighted by labor supply weights which are calculated as annual hours times population weights.

I complement the Census-based education measures by employing a set of variables reflecting different aspects of skills. From National Longitudinal Survey of Youth (NLSY) 1979 I get The Armed Forces Qualification Test (AFQT) score, which is widely used as a measure of general innate ability (Heckman, Stixrud, and Urzua, 2006). From 1983 to 1992 the survey reports AFQT scores as well as 3 digit 1980 Census occupation codes. After pooling observations in all years and using the crosswalk by David Dorn to match occupation classification used in this study, I calculate occupational mean AFQT scores weighted by customized longitudinal weights.

From the occupational network (O*NET) database published by the US Department of Labor I obtain the occupational Job Zone information which measures the occupation-specific training requirements. I translate the original intervalled variable to months of training using the table provided by O*NET. I further use three additional variables from the database as proxies for working conditions. One indicates how demanding a job is in terms of working time with a measure of "the typical length of workweek". The other provides a proxy for cognitive demands of the job by the variable "analyzing data or information". Last one is a combined measure of hazardous conditions of the job computed as an average of several related variables.[11] I merge the SOC 2010 codes provided by O*NET to the dataset using 2010 ACS's reported SOC codes and 2010 labor supply weights.

The last source of occupational data is Dictionary of Occupational Titles (DOT) 4th edition. I employ general educational development (GED) and specific vocational preparation (SVP) as alternative skill intensity measures. GED for a particular occupation is given by the highest score out of three categories (reasoning, math, language) each of which is computed in a 6 point scale. SVP provides a more job-specific measure which only includes the training (acquired in school, work, military, institutional or vocational environment) in order to achieve the average performance of the tasks required by the occupation. It does not include schooling without vocational content. I use a version of this variable which translates the 9 point scale of the original variable into training time in months. The dataset I utilize reports the mean DOT variables for Census 1980 occupation codes is prepared by England and Kilbourne (1988). I merge 1980 Census occupations to my occupational dataset using 1980 Census labor supply weights and the crosswalk provided by David Dorn. In addition I use the relevant aspects of the three-task view (abstract, routine, manual) computed from DOT in a similar way by Autor and Dorn (2013).

11 Following variables are included in the hazard measure: "Deal With Physically Aggressive People", "Deal With Unpleasant or Angry People", "Exposed to Contaminants", "Exposed to Disease or Infections", "Exposed to Hazardous Conditions", "Exposed to Hazardous Equipment", "Exposed to High Places", "Exposed to Minor Burns, Cuts, Bites, or Stings", "Exposed to Radiation", "Exposed to Whole Body Vibration", "Extremely Bright or Inadequate Lighting", "Very Hot or Cold Temperatures".

3.3 Occupational Skills and Trends in Occupation Growth

3.3.1 U-Shaped or Monotonic?

In the literature almost all of the evidence for polarization comes from skill percentiles represented by mean or median wages. If the skill-based interpretation of polarization is true then we expect to confirm it using more direct measures for skills too. The key skill classification in the literature on SBTC is based on college education. Therefore, I simply start reassessing the role of skills in changing labor market trend by comparing occupational employment and wage growth patterns when occupations are ranked by mean wages to rankings based on high-skill worker intensity. Two alternative variables capture the skill intensity. The first one, college worker share, is the ratio of employment of workers with any college education to the occupation's total employment. The second, college graduate share, is the intensity of workers with at least a college degree in occupation's employment. Figure 3.2 presents the growth pattern of occupation employment and wages based on the three alternative measures of occupational skill. Panel A and Panel B plot the smoothed employment share changes and real hourly wage growth by the skill percentiles in the 1980 US labor market. Small diamonds in the figure correspond to changes by mean wage ranking and confirm the polarization for the US between 1980 and 2010 in both of measures occupation growth. Comparison with Autor and Dorn (2013) who report a similar figure for 1980-2005 period reveals that the last half of the 2000s did not impose a significant change in the long-run polarization outlook.

In the same figure the evolution of occupational employment share and real wages can also be tracked when skill percentiles are formed by high-skill intensity variables. Both relative employment and wage growth of occupations follow monotonic paths along skill percentiles, which strikingly contrasts with the u-shaped growth suggested by wage percentiles.

A further remark from the figure is that the trend in occupation growth is almost identical according to both high-skill intensity variables. This is not completely surprising, but there are reasons for potential divergence. One reason could be that many workers with some college education but without a degree, which *arguably* does not add too much over a high-school degree compared to a college degree, are concentrated in some of the least paying jobs such as babysitters and waiters. Therefore college worker share could persistently rank this type of jobs towards the middle of distribution while college graduate share, similar to mean wages, might have suggested a lower place in the skill/quality hierarchy of occupations. Evidence in Figure 3.2 excludes such concerns.

Figure 3.2 leads to a puzzle when considering the consensus view on labor market polarization. From the perspective of SBTC, however, the interpretation could not be clearer. Just as the demand for high-skill workers, the relative demand for occupations that employ better skilled employees has increased over the last decades. However, it is too early to rule out the skill-based interpretation of polarization by looking at Figure 3.2. Important questions are whether other measures of skills beyond college education are supporting the polarization observation, and whether the observed skill-biased occupation growth is driven by a certain decade, gender, age group or the choice of occupational classification. In the remaining part of this section, I clarify the role of skills in the changing structure of occupational employment from several angles and shed light on the sources of the contrasting patterns.

3.3.2 Choice of Skill Measure

College worker or college graduate share of employment are relevant metrics for skill intensity from the lens of SBTC hypothesis, but there are other direct measures of skill intensity to check the external validity of the observations in Figure 3.2. Investigating the robustness of the monotonicity observation with other skill measures can also help understanding the contrasting patterns. For instance, a concern on college intensity measures can be that the skill quality in the lower parts of wage distribution is low because of the high share of dropouts so that the college intensity variables do not sense the difference between a high school graduate working in a middling job and a worker in the lowest-paid job with just a few years of schooling. Figure 3.3 addresses this matter by utilizing a continuous education measure, mean years of schooling.

The smoothed employment share change (Panel A) and wage growth (Panel B) provide evidence in favor of the results based on high-skill intensity in the previous figure. Though, the tendency of occupation growth is not strictly increasing according to mean years of schooling. This is not in contrast with SBTC since the hypothesis does not claim an increasing demand for every year of education. Nevertheless, the linear prediction of the smoothed changes, shown by the continuous line surrounded by the 95 percent confidence interval in Figure 3.3, can successfully represent the pattern as the R^2 in both panels are above 0.90 and the linearity is statistically significant.

The visual evidence provided above is clear and shares a common methodology to similar studies on labor market polarization. However, construction of percentiles and smoothing procedure can potentially exaggerate the difference between results by wage and education rankings. In addition, it is of interest whether skill measures beyond formal schooling also align with monotonic demand shift towards more skill intensive occupations. Therefore, I formally test the hypothesis whether occupation growth in employment and wages fit better to a u-shaped or linear relationship with respect to skill measures with regressions in the spirit of Goos and Manning (2007).

In particular, I estimate the following for testing the u-shape:

$$\Delta d_j = \gamma_0 + \gamma_1 s_j + \gamma_2 s_j^2, \tag{3.44}$$

where Δd_j denotes occupation j's change in employment share or log real hourly wage over 1980-2010 period and s_j denotes the occupational skill measure. Alternatively, for testing the linear relationship I simply estimate equation (3.44) when $\gamma_2 = 0$.

Table 3.1 and Table 3.2 report the regression coefficients on several skill measures when the occupation growth measure is employment share change and real wage growth, respectively. Column (1) of both tables confirm the well-known u-shape with a negative and significant coefficient of the mean wage and a positive significant one for the quadratic term. The u-shape for employment share change in Table 3.1 is not only significant but strong as suggested by rejection of a simple linear relationship due to the insignificance of the linear term alone in column (2).

Columns (3) to (6) of both tables reestablish the significance of a linear positive relationship between employment share changes and initial mean college share of employment or years of schooling, and further suggest rejection of a u-shaped relationship in line with the evidence provided in previous figures.

The evidence presented so far clearly marks the contrast between wages and education variables in interpreting the direction of occupational demand changes. Yet it may not be sufficient to perfectly overturn the skill-based interpretation of polarization due to two reasons. First, there is unobserved heterogeneity in the quality of education, and the quality of workers is directly reflected into average wages. Therefore wages could reflect the true skill intensity of an occupation better than education variables. This concern is addressed in the regressions by introducing the AFQT scores for each occupation. AFQT is designed to measure trainability and widely used as a cognitive skill measure in the literature. Assuming that workers with high AFQT represent better qualities in the market and more likely to end up in better-paid jobs, using this measure sheds light on whether poorly reflected quality by education variables is the main driver of contrasting occupation growth patterns. According to columns (7) and (8) of both tables employment share change and wage growth are significantly characterized by a linear positive relationship and not u-shaped with respect to cognitive skill intensity.

The second concern on the education measures of Census can be that while they show the obtained education they could mask the education required to perform the job. A low-wage occupation may employ workers seemingly as skilled as in the middle-pay one, but if the required level of ability is lower in the low-wage job for the same level of skill compared to middle-wage one, then observed skill intensity again overestimates the true ability proxied by wages. Similarly, the middle-wage occupations can also look artificially less skill-intensive if they require education/training on the job while low wage jobs do not. This alternative is tested in columns starting with (9) in both tables by three measures developed to quantify the actual *required* skill intensity of jobs. The first is GED variable from DOT. It measures the formal and informal aspects of education that shapes the worker's ability in several dimensions to perform the task. It is a measure of training requirement that involves general skills including but not limited to formal education. The other two focus on the required occupation-specific training from two different sources introduced in the data section: SVP from DOT and JZ from ONET. The former is indicated as Training (DOT) and the latter as Training (O*NET) in the tables. In all alternative specifications for both employment share and wage growth equations, there is no evidence of a significant u-shaped pattern. On the contrary all variables perform better in the linear framework. A wide range of skill variables suggest that growth of occupations goes hand in hand with skill intensity.

The long run pattern for the dynamics of employment and wages across occupations depends crucially on the metric used to measure skill. Polarization is an outcome only when skill is measured by occupational wages. All other metric for skills, namely share of college workers, college graduates, mean years of education, ability, skill requirement, and training, deliver a significant monotonic pattern. The implication of these findings is that the skill-based interpretation of polarization should be approached with caution. In the following, I dig deeper to establish the robustness of this observation across time, gender and age groups, and then by occupational classification.

3.3.3 Growth Patterns by Decade and Demographic Groups

3.3.3.1 *Occupation Growth in Each Decade*

SBTC hypothesis predicts a continuously increasing demand for the more educated. If relative demand changes at occupation level also move in a similar way, then I expect to observe the monotonic employment share and wage changes not only in the long-run but also in smaller frames of time. Figure 3.4 plots the tendency of employment share changes in each decade from 1980 to 2010 by skill percentiles according to the mean college share in 1980. It should be noted that there is a fall in the strength of linearity of the tendency after 2000, which can be seen by comparing smoothed changes with their linear fit at the Panel C of the figure. Also both the coefficient of each skill percentile and the R^2 decrease in each following decade. Nevertheless, the monotonically increasing pattern for employment growth is confirmed for each decade after 1980.[12]

Figure 3.5 performs the decadal analysis this time for wage growth. As in employment share change figures, the long-run pattern of occupation growth proportional to skills can be validated within each decade. The monotonicity is slightly violated for the lowest decile of distribution in 1980s and 1990s, which is yet far from implying polarization. Also, in 1990s the wage growth of lower skilled percentiles is higher than their growth in 1980s and 2000s. However in 2000s the monotonic wage growth comes back even stronger as the smoothed changes is perfectly indistinguishable from their

12 Two related papers (Autor, Katz, and Kearney, 2008; Autor, Katz, and Kearney, 2006) observe polarization according to both wage and years of education percentiles during 1990s, which contrasts with the evidence provided here. In appendix section 3.C I discuss the issue in detail and provide evidence showing that the contrasting results stem mainly from the choice of occupational classification.

linear fit. Figures 3.4 and 3.5 jointly support the continuity of skill-biased demand growth at occupation level.

3.3.3.2 *Occupation Growth in Gender Groups*

The literature provides plentiful evidence that the aggregate demand for skilled workers increases regardless of gender. Therefore, it could be expected that the monotonic growth pattern also holds within gender groups. On the other hand, recent papers argue that growth trends in the disaggregate sections of the economy has been affected by female workers (e.g., Cerina, Moro, and Rendall, 2017; Ngai and Petrongolo, 2017). In order to see if the occupation growth with respect to skills differs by gender, Figure 3.6 plots smoothed changes by college share of employment when the labor market is split by gender. Both employment and wage growth clearly indicate that the monotonic wage and employment changes take place within both gender groups.

The figure provides additional insights regarding the evolution of gender gaps. In Panel A, employment share of occupations at the upper half of skill distribution increases for both genders at the expense of jobs with lower skill intensity. The shift towards higher skilled occupations is sharper in female employment suggesting that female workers are increasingly represented in skill intensive jobs. While wage growth by gender shown in Panel B is in line with the key observation in this study, it is also possible to track the narrowing gender wage gap from the figure. The change in women's occupational wages tend to be above men. At the same time, wage growth in both gender tend to converge towards higher occupational skill intensity. Both panels therefore imply the previously documented slowdown in the narrowing wage gap after 1980s from a different perspective: women are disproportionately allocated into higher skilled jobs where their wage growth is more similar to men.[13] The implication of this from the occupational perspective is that women are improving the quality of their representation in the labor market which simultaneously comes with a slowdown in the closing rate of gender wage gap.[14]

13 Among others see Blau and Kahn (2006) for the narrowing of the wage gap and slowing down after 1980s and Goldin, Katz, and Kuziemko (2006) for the disappearance of the gender college gap in the US.

14 Goldin (2014) documents that convexity in hourly earnings with respect to working hours plays a role in the slowdown. The famous examples of jobs characterized by wage-hours convexity are among the ones of highest skill intensity.

3.3.3.3 *Occupation Growth in Age Groups*

The behavior of age groups is potentially related to the growth patterns of occupation employment and wages for a number of reasons. First, the demographic structure of the US labor market is significantly affected by the baby-boom cycle. Following the initial decline, the post-1980 period witnessed a sharp increase in the relative supply of experience in both high- and low-skilled labor market (Caselli, 2015). A possible implication is that older workers in the economy can drive occupation employment growth in the skill-intensive occupations if they have a comparative advantage in these jobs. Furthermore, if there is experience-biased technical change then also the wages in these jobs may contribute to the relative wage growth.[15] If this channel is strong enough to drive monotonicity in the entire labor market, then upper tail growth should be dominated by relatively older age groups.

Second, occupational reallocation of employment is potentially associated with the changing age-structure of occupations. In particular, Autor and Dorn (2009) observe that routine-intensive occupations are becoming older. As a result, other occupations might have been growing solely on the shoulders of younger workers flowing out of the routine-intensive jobs. It would be consistent with this argument to observe that the monotonic growth by skills is driven by employment of relatively younger groups.

In order to address age-related concerns on the key observation of the paper, I plot smoothed occupation growth of employment share and wages for three age groups in Figure 3.7. Panel A shows employment share change by skills. As opposed to the first concern, the upper tail growth is not particularly confined to older age groups. On the contrary, the employment share growth for the young-age group is significantly higher above the 80th percentile. In contrast to the second concern, it does not seem that young workers play a special role in employment share changes as they evolve very similarly throughout most of the skill distribution.[16]

Panel B presents the occupational wage growth by skills with respect to the three age groups. The figure suggests evidence in favor of the experience-biased technical change as the wage growth tends to be higher for older groups. Aggregate pattern observed in wage growth by skills is also not particularly driven by any of the groups. The only violation to monotonicity is seen for prime age and older groups confined

15 The term is introduced by Caselli (2015).

16 The exception is for occupations of highest skills. However, this is not predicted by the routine-biased technical change model, where workers that are employed (or can potentially work) in routine-intensive jobs are reallocated in the low-wage services occupations (Autor and Dorn, 2013).

to the last 5 percentile of employment. Moreover, the size of twist at the bottom of distribution is limited in size.[17]

In sum, the evidence across time and demographic groups suggests that occupation growth in favor of relatively skilled occupations is a pervasive fact of the US labor market.

3.3.4 Sensitivity to Occupational Classification

All the analysis so far is performed using the occupational classification of Dorn (2009). In addition there are two more occupation categories provided by IPUMS Census that are comparable across Census waves, namely *occ1950* and *occ1990*.[18] These two classifications are inclusive of all the existing occupations but are not balanced in the sense that some occupations in later years do not exist. David Dorn's classification, *occ1990dd*, is an improved version of Meyer and Osborne (2005)'s modification on 1990 Census 3-digit occupation codes (*occ1990*) and provides a balanced set of occupations. Nevertheless, it involves merging of more detailed Census occupation codes and this has the potential of affecting the results. Therefore in order to enable comparison, in this subsection I present the graphical analysis regarding different occupation codes suggested by Census.

Figure 3.8 shows long run smoothed employment share and wage changes by skill percentiles of college share of employment in 1980 calculated according to different occupation classifications. Under all classifications I confirm the key long-run observation of monotonic occupation employment and wage growth by skill intensity.

Since skill-biased occupation growth is a robust observation it is important to understand the sources of contrast with the polarization observation, which is the aim of the following subsection.

17 Quadratic polynomial fit of wage changes by prime and older groups are not statistically different from the linear fit.

18 See Meyer and Osborne (2005) for a related working paper that provides a comparison of two classifications in depth.

3.3.5 Occupational Wage Structure

Why do we observe polarization by wages but not by other skill measures? The answer partially lies in the strength of the connection between wages and direct skill measures for low and high wage jobs, on which Figure 3.1 provides an early insight: occupational wages in 1980 reflect skills well for the upper half of wage distribution, whereas the occupations' pay structure in the lower part is different than what is predicted by their skill intensity. This is important in skill-based interpretation of polarization since occupational wages are treated as a one dimensional index of skills (Goos and Manning, 2007).

In order to formally test this, I present in Table 3.3 the partial correlates of wages in both halves of wage distribution using the set of occupational skill measures introduced above. To enable comparison across specifications by different skill variables I use the percentile rank of variables in regressions. In all cases wages correlate well with skill measures for the upper half of wage distribution (Panel B) and show no significant correlation for the lowest paying half of jobs (Panel A). Additional observations can be made from the table. First, the reported coefficients are small and insignificant for the lower half of wage distribution and the R^2s are too small. Second, training variables have a higher coefficient compared to education variables and AFQT in low wage occupations which implies that firm-specific training possibly have some weight in occupational wage determination but the association is imprecisely estimated and much smaller compared to the high wage group.

Therefore in the determination of occupational wage structure, skill intensity does not appear to play the leading role particularly for the low-wage jobs, which clearly suggests that the rising employment demand in low-wage occupations does not imply a trade-off between middle-skill and low-skill workers but something else. The literature on polarization often associates skill types with certain tasks. While majority of the models assume a hierarchy of skill types, task-specific skills that have different labor market price might also lead to the observed wage structure (see Barány and Siegel, 2017, for an example with sector-specific skills).

Therefore as an alternative predictor of the wage structure, I turn to the three-task view of routinization hypothesis (Autor, Katz, and Kearney, 2006). According to the three-task view manual jobs have relatively lower productivity so that labor market return to working in those jobs is also low. On the other hand, abstract tasks involve a lot of complex thinking and interactions which are needed to solve the hardest problems and have the highest returns. Cognitive or non-cognitive routine tasks require precision which puts those jobs somewhere in between and dominates the middling jobs. Consequently, one expects to see the wage structure to associate negatively to manual task intensity and positively to routine task intensity for the lower half of the distribution. Furthermore, the upper half of the wage structure should be increasing in abstract intensity and decreasing in routine task intensity. Similarly, the combined routinizability measure of Autor and Dorn (2013), RTI, which jointly reflects routine, non-manual, and abstract task intensity should be increasing along the lower and decreasing along the upper half of the wage structure.

In Table 3.4 I run occupational wage regressions this time on the task characteristics. First three columns show the association of three task aspects in Autor and Dorn (2013) with wages in the upper and lower half of occupational wage structure. Abstract task content and wages are positively related as expected but not significantly for the low wage jobs. Routine task intensity is positively related to wages for low wage jobs and inversely for high wage group as expected but lacks significance. Contrary to the stylized view I do not find a declining wage structure with manual task intensity for the low-wage jobs. Column (4) of panel A of the table shows an unexpected negative association of combined routine task intensity measure of Autor and Dorn (2013) with the lower part of wage structure. The stylized three-task view is also incapable of capturing the 1980 wage structure at detailed occupation level.

Another task driven wage structure explanation is provided by compensating wage differentials literature (Rosen, 1974, 1986). In this explanation wages are higher if a job requires a less desired task performance requirement, e.g. it is more difficult, riskier and demanding. In the last three columns of Table 3.4 I use three task measures to quantify how demanding a job is. The first measure is on the time demand of the job proxied by the O*NET work context variable "Duration of Typical Work Week". The second one is a measure of cognitive demands of the job. I proxy this aspect by O*NET work activity variable "Analyzing Data or Information". The last one measures the hazard involved in the performance of a job by a combination of O*NET variables introduced in Section 3.2. These three capture the opportunity cost of leisure, the cost of mental effort, and the riskiness of the task, all of which are potentially related to wellbeing of the worker and often dictated by the working conditions. All three of the measures correlate well with wages for low wage group. For high wage occupations all continue to have a positive association except hazardous conditions.

Obviously, these simple OLS regressions do not intend to prove that wages are solely determined according to compensating differentials, but just to show that the skill-based interpretation of polarization remains too naive in assuming lowest skills for occupations of lowest wages. One can find more task-specific aspects that accord with occupational wages better than skill measures, or argue that occupational wages reflect occupation-specific innate ability in the spirit of Roy-type models. All of these potential explanations for why occupational wages and general skill intensity do not overlap at the bottom half of distribution are essentially unrelated to the increasing relative demand for college workers.

The main message from the correlations shown here is that in 1980 the wage structure was not strongly determined by the skill intensity. This sheds light on why skill-based interpretation of labor market polarization does not hold. To the extend that skill intensity and task-specific attributes of jobs deviate in the determination of occupational wages, it becomes harder to observe similar patterns in occupational demand growth by wages and by skills.

3.3.5.1 *Distribution of Skills Across Broader Occupation Groups*

The three-skill view of polarization on broader occupation groups suggests distinct roles for some of them. According to this perspective, management, professional and technical jobs are the highest skilled and dominate the top wage distribution. These experience the greatest increases in employment demand. The middle-wage jobs involve production, crafts, transportation, mechanics, operators as well as clerical and office workers whose importance in the labor market sharply declines. The lower tail of wage and skill distribution is occupied by service occupations. Autor and Dorn (2013) show that this last group is responsible from the polarization of the employment demand at the lower half of distribution in the US.[19] Here I present evidence using different skill measures to improve the insights from the broken wage-skill association for lower skilled occupations documented above.

Figure 3.9 shows the smoothed local means of skills by occupational wage percentiles in 1980 for the set of skill variables regarding six major occupation categories.

19 For Europe similar observations regarding the role of low wage service occupations are made by Goos and Manning (2007) and Goos, Manning, and Salomons (2009, 2014).

Calculations are weighted by the 1980 employment share reflecting local means according to labor market importance. Two facts stand in contrast with the stylized three-skill view. First, skills in the service occupations are not very much different than many of the middle-wage occupations. For the lowest wage percentiles where service occupations are the most important regarding polarization, they are never the least skill-intensive occupation group. This observation does not depend on the skill aspect. Education, cognitive capacity or training requirement measures all suggest that low-wage service occupations exhibit skills at least as high as middling occupations except clerical/sale occupations. Second, clerical occupations exhibit the highest skills among middling jobs despite the fact that they get the lowest wages after service occupations. According to most skill measures these jobs are quite close to top wage jobs in terms of skill intensity.

3.3.6 The High-skill Worker and Polarization

An important implication of the skill-based interpretation of labor market polarization is that high-skill workers are seen as negligible in the reallocation of employment towards the low-wage jobs. In the literature this assumption can be as stark as completely ignoring college workers in the growth of low wage and the decline of middle wage jobs (Autor and Dorn, 2013). Here I briefly argue that the evidence suggests the contrary.

Figure 3.10 shows the 1980-2010 employment share growth of major occupations for college and non-college employment share ranked according to their 1980 wages. Each skill type is separately treated. Darker bars show the growth of non-college employment and lighter bars represent growth rates calculated for college worker employment share. The figure suggests that employment in major occupation groups homogeneously polarizes regardless of the skill category. Workers of both skill type reallocate towards the tails of distribution. An analysis of polarization should therefore involve the presence and growth of high skill workers not only for the top paying jobs but everywhere in the labor market.

3.3.7 Summary of the Empirical Results

I briefly summarize the key findings of empirical section here. First, employment and wage growth of occupations is increasing in the skill intensity while they follow u-shaped pattern by occupational wages. The skill-biased employment and wage growth of occupations is robust to the choice of skill measure and not particularly driven by a specific decade, gender, age group, or occupation classification. Second, the wage structure in 1980, specifically at the lower half, does not reflect the skill structure of occupations. Rather, task-specific working conditions do a better job in lining up with the wage structure. Third, clerical/sales and service occupations tend to have higher skill intensity throughout the wage distribution although they are paid the lowest wages. Fifth, college and non-college workers seem to take their part in the polarization of employment in every major occupation group. The evidence as a whole suggests that the dispersion in the within-occupation heterogeneity of skills provides valuable information regarding the characterization of trends in occupation growth. In terms of modeling, the results suggest skill-biased technical change at occupation level. In order for this to be consistent with the polarization along the mean wage of occupations, one should include both general skills and other dimension of work conditions, amenities or some form of occupation-specific technical change.

3.4 A Model of SBTC Within Occupations

3.4.1 The Model

3.4.1.1 *Overview*

The model is an extension of the canonical SBTC model of Katz and Murphy (1992). The environment is essentially static and exogenous technical change is assumed. There are two types of worker skills which are imperfect substitutes and both contribute to the production of the task output of an occupation. The same task could be performed by both skill types though the skill intensities across occupations differ according to the importance of each skill type for the task output. For surgeons the weight of high skilled in the production function can be assumed as maximum so only college workers can perform the job whereas for artists it can be lower, reflecting the fact that some of this activity could be performed by non-college workers. These weights can change but since skill structure is very stable in the long term, I assume them as fixed.[20]

Occupations' task output are combined in an aggregate production function to produce the final output which is then consumed. There is a final good sector where all task production is used as inputs as imperfect substitutes. In sum, the production side of the model is simply an extension of the canonical model to include occupations. The crucial distinctive feature of the model compared to the recent task-based SBTC models (e.g, Acemoglu and Autor, 2011; Autor and Dorn, 2013) is the joint presence of both skill types in the production of the same task output. Therefore what makes occupational skills in this setting is the share or intensity of each skill type rather than the skill of a single type.

Wage inequality across occupations in the model is introduced through occupational variation of disutility from work (Rosen, 1986). This aims to account for the empirical observation in the previous section that the occupational wage structure does not accord well with the skill structure and more with task characteristics related to the disutility attached to the job such as time requirement of the job.[21] I assume the simplest form of compensating differentials such that workers are homogeneous in preferences and skills, which can be relaxed to have richer dynamics with respect to technology. For instance, one can further assume that workers of each skill type are heterogeneous in terms of their sensitivity to disutility. In this model, workers experience a different level of satisfaction depending on the type of job they choose, in addition to the consumption provided through wage income. In the following, I lay out each piece of the model as introduced above. Then I describe the equilibrium of the model followed by a study of the impact of technical change in this analytic framework.

20 See Figure 3.A.1 for stability of the occupational skill structure. The figure compares the wage and skill structure in 1980 and 2010. From the figure it is clear that skill intensity is quite stable both in absolute terms and also when compared to the wage structure in 1980 and 2010.

21 Another alternative to generate a wage structure that does not overlap with skill-intensity is to assume occupation-specific ability distributions as in Roy-type models.

3.4.1.2 *Final Good Production*

The aggregate production function at time t is the following:

$$Y_t = \left(\sum_{j}^{J} \gamma_j \left(T_{jt}\right)^{\rho} \right)^{\frac{1}{\rho}}, \tag{3.45}$$

where Y_t is aggregate output, T_{jt} is task output by occupation j and total number of occupations is J. $\gamma_j > 0$ is the occupation-specific constant weight in production and $\rho < 1$. $\frac{1}{1-\rho}$ is the elasticity of substitution across occupations.[22]

The representative firm in the final good market takes task prices p_{jt} as given maximizes profits by choosing task inputs optimally according to:

$$\max_{T_{jt}} \{Y_t - \sum_{j=1}^{J} p_{jt} T_{jt}\}. \tag{3.46}$$

3.4.1.3 *Task Production*

The task production function at time t for occupation j is given by:

$$T_{jt} = \left((\beta_j)^{(1-\mu)} \left(A_{Ht} H_{jt}\right)^{\mu} + (1-\beta_j)^{(1-\mu)} \left(A_{Lt} L_{jt}\right)^{\mu} \right)^{\frac{1}{\mu}}, \tag{3.47}$$

where H_{jt} and L_{jt} is the labor input by high-skill and low-skill workers respectively. There is no endogenous skill choice so total labor supplies H_t and L_t are exogenous in the model as in the canonical model of SBTC. $0 \leqslant \beta \leqslant 1$ measures occupation- specific skill intensity, and $\mu < 1$. The elasticity of substitution between skilled and unskilled workers that is constant across occupations is given by $\frac{1}{1-\mu}$. A_{Ht} and A_{Lt} represent skill-specific technologies which potentially grow in different and constant rates. In the SBTC literature, the bias of technology in favor of skills usually refers to the case when high-skill technology grows faster than technology of low-skill workers.

The representative firms in each task market maximize profit by choosing skill inputs optimally according to:

$$\max_{H_{jt}, L_{jt}} \{p_{jt} T_{jt} - w_{Hjt} H_{jt} - w_{Ljt} L_{jt}\}. \tag{3.48}$$

22 If one assumes a time varying version of γ_j one can also study occupation-specific demand shifters with this model.

3.4.1.4 *Households*

The consumer side is characterized by the following utility function for each worker with skill level S working in occupation j:

$$U_{Sjt} = \log(C_{Sjt}) - \log(d_j), \tag{3.49}$$

where C_{Sjt} is consumption of final output by worker of skill $S = \{H, L\}$ who works in occupation j at time t. d_j is occupation-specific disutility of work. It is higher in jobs that are more demanding than others which reflects difficulty or risks associated with the task. The utility of worker of a given skill depends on the occupation decision.

Since the model is static there is no saving and the wage earned from working in occupation j is fully consumed:

$$C_{Sjt} = w_{Sjt}, \tag{3.50}$$

where the wage w_{Sjt} is the same for all workers of the same occupations and in the same skill group due to worker homogeneity.

3.4.1.5 *Equilibrium*

An equilibrium at time t is defined by allocations of the labor of each skill group across occupations $\{S_{jt}\}_{j=1}^{J}$, and the consumption choices of workers of each skill type $\{C_{Sjt}\}_{j=1}^{J}$, occupational wages for each skill group $\{w_{Sjt}\}_{j=1}^{J}$, and prices of task output $\{p_{jt}\}_{j=1}^{J}$ given fixed occupation weights in final output production $\{\gamma_j\}_{j=1}^{J}$, high skill weight in task production $\{\beta_j\}_{j=1}^{J}$, occupation-specific disutility parameters $\{d_j\}_{j=1}^{J}$, skill supplies H_t, L_t and skill-specific productivity $\{A_{Ht}, A_{Lt}\}_{j=1}^{J}$ such that:

1. Workers choose the occupation that yields the highest utility.
2. The representative firm of final output optimally chooses the task input T_{jt} for each occupation j according to (3.46), and task producers in each occupation optimally choose high-skill (H_{jt}) and low-skill (L_{jt}) labor input following (3.48).
3. Occupational wages clear the labor market so that $H_t = \sum_{j=1}^{J} H_{jt}$ and $L_t = \sum_{j=1}^{J} L_{jt}$.
4. All output is consumed so that $\sum_{j=1}^{J} \left(H_{jt}C_{Hjt} + L_{jt}C_{Ljt}\right) = Y_t$

3.4.2 Occupational Wage and Skill Hierarchy, and Their Stability

Working in some occupations yields lower utility. Therefore in an equilibrium where a positive level of employment exists in each occupation, workers should be indifferent between occupations. This implies that differences in disutility should be compensated by wage:

$$\frac{w_{Sjt}}{d_j} = \frac{w_{Sj't}}{d_{j'}}. \tag{3.51}$$

Equation (3.51) suggests that conditional on skill-type the wage ordering is given by disutility parameters. On the other hand, occupational wage structure (employment-weighted average of wages in each occupation) is not independent from the skill specialization of occupations. An occupation can offer lower wages compared to another one in both skill types but the average wage can still be higher because of the share of high-skill workers.[23] This can be seen by comparing the mean wages in two arbitrary occupations:

$$\frac{w_{jt}}{w_{j't}} = \frac{\frac{H_{jt}}{H_{jt}+L_{jt}} w_{Hjt} + \frac{L_{jt}}{H_{jt}+L_{jt}} w_{Ljt}}{\frac{H_{j't}}{H_{j't}+L_{j't}} w_{Hj't} + \frac{L_{j't}}{H_{j't}+L_{j't}} w_{Lj't}} = \left(\frac{d_j}{d_{j'}}\right) \left(\frac{\frac{H_{jt}}{H_{jt}+L_{jt}} w_{Hj't} + \frac{L_{jt}}{H_{jt}+L_{jt}} w_{Lj't}}{\frac{H_{j't}}{H_{j't}+L_{j't}} w_{Hj't} + \frac{L_{j't}}{H_{j't}+L_{j't}} w_{Lj't}} \right), \tag{3.52}$$

where w_{jt} is the mean occupational wage calculated as the employment-weighted average of the wages of skill-types in an occupation. The second part of the equation is derived using the wage indifference condition. From equation (3.52) it is clear that less desirable working conditions increase the average wage, and the relative share of high-skill workers is another determinant. For instance, a less demanding job on average could yield higher wages compared to a job with more challenging attributes if it is sufficiently more skill intensive. Hence, the wage structure of occupations depend on the skill structure too.

Another implication of the model on occupational wage structure is related to its stability. Inspection of equation (3.52) also suggests that relative wages are affected by the increase in high-skill wage premium. Therefore it is possible to have signifi-

23 I implicitly assume here a higher relative wage for the high-skill worker in each occupation. This can be given by assuming a level of relative technology $\frac{A_{Ht}}{A_{Lt}}$ that is sufficiently low or high depending on the sign of μ.

cant changes in the wage structure as the premium rises since skill intensity across occupations are different.

The model's implication on the skill structure, however, is relatively straightforward. Using the indifference condition and the first order conditions of task production for each occupation and skill type the following is derived:

$$\frac{\beta_j}{\beta_{j'}} \frac{1-\beta_{j'}}{1-\beta_j} = \frac{H_j}{H_{j'}} \frac{L_{j'}}{L_j}. \tag{3.53}$$

Equation (3.53) implies that the relative skill intensity hierarchy across occupations is constant. The supply of skills H_t and L_t might be subject to change, yet this is never translated into a change in the relative skill intensities. Furthermore occupations' skill structure is pinned down simply by βs independent of the occupations' wage. Given a set of skill intensity parameters the equation predicts a stable occupational skill structure.

In fact the model's prediction for stable skill structure and potentially changing wage structure is confirmed by the long-run comparison of occupational rankings based on average wages and share of high-skill worker in Figure 3.A.1. Occupational wage ranking in 1980 is correlated to ranking in 2010 although there is substantial change for some occupations. On the other hand, occupational ranking based on high-skill share looks quite stable in the long-run.

3.4.3 The College Wage Premium

It is possible to derive the aggregate skill premium that nests the equation suggested by the canonical SBTC model. The skill premium equation is given by the ratio of economy-wide high skilled wages to low skilled wages both of which are calculated as the mean wage for the corresponding skill group weighted by occupations' employment share. Using the first order conditions of optimal task production the skill premium equation can be expressed as follows:

$$\log\left(\frac{w_{Ht}}{w_{Lt}}\right) = \log\left(\frac{\beta_1}{1-\beta_1}\right) + \mu \log\left(\frac{A_{Ht}}{A_{Lt}}\right) + (\mu-1)\log\left(\frac{H_t}{L_t}\right) + \Gamma_{HLt}, \tag{3.54}$$

where $\Gamma_{HLt} = (\mu - 1)\log\left(\frac{\alpha_{H1t}}{\alpha_{L1t}}\right) + \log\left(\frac{\alpha_{H1t}+\left(\frac{d_2}{d_1}\right)\alpha_{H2t}+\cdots+\left(\frac{d_J}{d_1}\right)\alpha_{HJt}}{\alpha_{L1t}+\left(\frac{d_2}{d_1}\right)\alpha_{L2t}+\cdots+\left(\frac{d_J}{d_1}\right)\alpha_{LJt}}\right)$, and $\alpha_{Sjt} = \frac{S_{jt}}{S_t}$ for $S = \{H, L\}$.

The skill premium equation resembles the premium equation of the canonical model in terms of the two forces that is expressed as the race between education by Tinbergen (1974), namely the relative growth of skill-specific technology (relative skill demand) and of relative skill supply. The evolution of skill premium differs from the canonical model because of the last term on the right hand side. It captures that in the occupation augmented SBTC model there are two additional potential sources which can affect the aggregate skill premium. First is the changes in the ratio of high skill to low skill employment in each occupation, second is the changing representation of relative skills across occupations. These are directly related to the extensions this model has over the canonical one. Consequently, equation (3.54) is identical to canonical SBTC model if skill intensity parameter β and disutility parameter d are identical across occupations.

3.4.4 Technical Change and the Evolution of Occupational Demand

In this part of the section I study the implications of the model on occupational wage growth and reallocation of labor. Since the model is static, the results are based on assumptions on the direction of the technical change following the literature. Skill-biased technical change when combined with the model's key feature of skill heterogeneity within occupations, appears as a fundamental driver of the occupational reallocation of labor. The simple reason is that substantial bias of demand growth towards high-skill workers may also increase the demand for tasks that welcome high-skill workers relatively more. As a result SBTC acts as an occupation-specific demand shifter in the economy. The following proposition summarizes the model's results on changes in occupational labor demand, which brings together the key empirical observations of the previous section.

PROPOSITION 1: *Suppose that* $\frac{A_{Ht}}{A_{Lt}}$ *grows and* $0 < \mu < \rho < 1$*. Occupational employment share change and mean wage growth rate are increasing in skill intensity implied by* β_j *and do not depend on the wage structure. There exists a combination of disutility parameters* d_j *and skill intensity parameters* β_j *so that employment share changes and mean wage growth implies polarization, i.e., higher growth of employment and mean wage at the tails of wage structure relative to middle.*

I provide the formal proof in Appendix section 3.E and an intuitive discussion here. The economic forces shaping the reallocation of employment and the wage growth easily fit in the framework of SBTC. Suppose as in the canonical SBTC model that technical change is faster for high-skill worker and that different types of skills are gross substitutes in task production. Then demand increases towards the input which becomes relatively more efficient, and consequently the relative wages of high-skill workers increase. This is the relative demand force in the canonical SBTC model. In order for skill demand to translate into demand for skill intensive occupations a further assumption should be made on the substitutability of tasks in the production of output. If elasticity of substitution across tasks in the production of final output is larger than the elasticity of substitution between skills in task production, then the demand for more skill intensive occupation also rises more since that occupation produces at relatively increased level of efficiency thanks to the specialization towards more skilled workers. Therefore both the price of high-skill type and the task price of skill intensive occupations increase. This translates into higher growth of mean occupational wage in skill intensive occupations since the equally rising skill premium is reflected more heavily due to a greater share of high-skill workers. Note that in these results the key parameter is skill intensity, hence these results hold under any wage structure.[24]

The model does not strictly imply polarization. However, it is possible to observe polarization-like patterns along occupational mean wages if the least skill intensive occupations are positioned in the middle of wage distribution. As discussed in the previous part, the wage structure is given by a combination of disutility and skill intensity parameters. If the disutility parameters are low enough for jobs of moderate

24 Note that same qualitative results of the proposition hold under the alternative symmetric assumption such that $\frac{A_{Lt}}{A_{Ht}}$ grows and $\rho < \mu < 0$. Since the paper is not explicitly about modeling skills in the production function but concerned with the direction of the relative demand growth, I simply follow the SBTC literature in this assumption.

skill intensity, that is they welcome high-skill workers more than many other occupations while they are not among the least desirable ones, then the wage structure is subject to polarization of employment share changes and mean wage growth. This result is only a matter of how occupational wages are ordered, but if the ordering is suitable the driving force of the observed polarization is skill-biased occupational demand change of the model. Therefore, the model is capable of combining the key observation made in the section 3.3, that is monotonic growth by occupational skills simultaneously with polarization along occupational wages.

3.4.4.1 *Alternative Drivers of Occupation Growth*

The proposition suggests the economy-wide skill-biased technical change together with time-independent skill intensity differences across occupations as the driver of occupation growth in the economy. However, clearly there are other sources within the model's framework that affect the reallocation of employment and wage growth. First, the model can address the rise of the exogenous relative skill supply, which is an important part of the canonical model as a determinant of skill premium. In addition, in this model changes in the relative skill supplies have a distributional impact. Intuitively, when there are relatively more high-skill workers in the economy their allocation across occupations will be proportional to occupations' skill intensity parameter (equation (3.53)). As a result, the exogenous rise in the relative skill supply translates into higher productivity in occupations with higher skill intensity. This effectively has the same impact with SBTC in the model, hence both employment shares and mean wages change in favor of the relatively skill-intensive jobs. This alternative channel only strengthens the model's predictions. On the other hand, similar to the canonical model, relatively more high-skill workers in the economy has a negative impact on the skill premium (equation (3.54)) as $\mu < 1$.

Second, although introduced as fixed in the model the skill intensity parameter β_j can be subject to change. In this case, an additional impact comes from the alteration of the skill structure. In this case, occupations which improve their place in the skill intensity ladder relatively grow in size and wages. The stability of the skill-intensity over time (shown in Figure 3.A.1) suggests that this potential driver of occupation growth is very likely to have limited impact.

Figure 3.A.2 summarizes the occupational information on the two channels. The figure plots the 1980-2010 log change in skill intensity ($\frac{H_j}{L_j}$) against 1980 wages (upper

panel), and against 1980 skill intensity (lower panel). The evidence is in line with what is predicted by the model following an exogenous increase in relative skill supply while β_j is fixed for all occupations. The absolute change in skill-intensity is expected to be higher for more skill intensive occupations while percentage changes should be similar to keep the relative skill intensities constant. As a result, the log change in skill intensity should be a flat line with positive intercept, regardless of the ranking of occupations, which is close to the tendency of actual changes in skill intensity shown in the figure.

3.4.5 Predicting Labor Market Polarization by Skill Intensity

It is beyond the aim of this paper to quantify the impact of occupation-based SBTC in actual polarization, however suggestive evidence is presented here to complement the discussion. In order to illustrate how much the extended SBTC view introduced above can help to understand labor market polarization in addition to monotonic demand shifts, I perform a simple prediction with the data used in Section 3.3. I predict the employment share change and mean wage growth of major occupation groups between 1980 and 2010 using 1980 skill intensity of occupation groups.

Figure 3.11 shows the skill intensity-predicted and actual employment share changes in the upper panel, and mean wage growth in the lower panel, by 1980 mean wage of occupation groups on the horizontal axis. The dashed lines with rectangles represent actual changes of the corresponding variable. The solid lines with circles show the predicted change in employment share or mean log real wage. Employment and wage polarization are manifested by greatest increases in the high-wage management, professional, and finance as well as lowest paid clerical, and personal services occupations at the expense of middling occupation groups in both parts of the figure. A remarkably similar pattern is shown by the skill intensity predictions. Using occupation level measures of skills is promising in generating the non-monotonic trends observed in the labor market.

While predicted employment share and log wage changes are quite close to actual in general and exhibit the employment polarization pattern, the details in the figure provide additional insights. First, the predicted employment share change is a little higher than the actual for clerical and retail sales occupation group and lower for personal services occupations, which suggests that the rise of personal services can only be partially explained by skill-biased technical change. On the other hand, skill intensity can successfully capture the relatively higher growth of wages in clerical occupations, which is found as puzzling in routinization literature (Autor and Dorn, 2013).

3.5 Conclusion

In this paper I argue that occupational employment and wage growth trends in the US imply different patterns depending on the type of the metric for skills. The labor market polarization observed along occupational wage distribution after 1980 disappears when the skill measure is changed to other and more direct measures of occupational skill intensity based on education, cognitive ability, and training requirements. Instead, the occupational employment demand change fits better to a pattern where it continuously and consistently favors relatively skill intensive jobs almost monotonically, suggesting that the current extrapolation of labor market polarization onto the occupational skill space can be misleading.

I suggest an extension of the canonical SBTC model to occupations that can explain the skill-biased shifts of employment demand. If the level of wages are determined by occupation-specific factors rather than general skills, the model can also help understanding part of polarization phenomena. This does not rule out existing explanations of polarization based on occupation-specific demand shifters, namely institutional changes, routinization, international trade, and structural change. My results emphasize the importance of the high-skill worker in the changing structure of labor market even for jobs placed low in the occupational quality ladder. The findings presented here suggest that labor market polarization does not contrast with the growing demand for general skills in the labor market, but rather happens somewhat by virtue of it. My results are encouraging for future research, and potentially policies, on the connection between wage inequality and tasks from the perspective of working conditions, and on the determinants of observable skill intensity differences across occupations.

3.A Tables

Table 3.1: Employment Share Change and Skills

(Dependent Variable: Change in Occupational Employment Share, 1980-2010)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Wage	-8.05***	0.10												
	(2.87)	(0.28)												
Wage Squared	1.54***													
	(0.55)													
College Share			0.28	0.92***										
			(1.41)	(0.21)										
College Share Squared			0.65											
			(1.40)											
Years of Sch.					-0.11	0.12***								
					(0.51)	(0.03)								
Years of Sch. Squared					0.01									
					(0.02)									
AFQT							-0.23	0.13***						
							(0.34)	(0.04)						
AFQT Squared							0.04							
							(0.03)							
GED									-0.51	0.21***				
									(0.60)	(0.07)				
GED Squared									0.10					
									(0.08)					
Training (DOT)											0.01	0.06		
											(0.13)	(0.04)		
Training (DOT) Squared											0.01			
											(0.02)			
Training (O*NET)													0.22**	0.11***
													(0.10)	(0.03)
Training (O*NET) Squared													-0.02	
													(0.01)	
Constant	10.20***	-0.46	-0.44*	-0.54***	-0.23	-1.70***	0.03	-0.84***	0.35	-0.96***	-0.27*	-0.32**	-0.52***	-0.40***
	(3.71)	(0.80)	(0.23)	(0.15)	(3.33)	(0.42)	(0.82)	(0.24)	(1.09)	(0.26)	(0.16)	(0.14)	(0.18)	(0.14)
Observations	322	322	322	322	322	322	321	321	322	322	322	322	322	322
R^2	0.06	0.00	0.13	0.12	0.10	0.10	0.08	0.07	0.08	0.06	0.03	0.02	0.09	0.08

Notes: Each column shows the coefficients estimated by OLS from the regression of 1980-2010 occupational employment share changes on the corresponding skill measure shown in the rows. Wages, years of schooling and college share are computed from 1980 Census. See text for variable definitions. Regressions are weighted by occupations' 1980 employment share. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3.2: Wage Growth and Skills

(Dependent Variable: Change in Mean Log Real Wage, 1980-2010)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Wage	-1.49***	0.09*												
	(0.55)	(0.05)												
Wage Squared	0.30***													
	(0.11)													
College Share			1.00***	0.38***										
			(0.18)	(0.06)										
College Share Squared			-0.63***											
			(0.21)											
Years of Sch.					0.27***	0.05***								
					(0.10)	(0.01)								
Years of Sch. Squared					-0.01**									
					(0.00)									
AFQT							0.06	0.07***						
							(0.05)	(0.01)						
AFQT Squared							0.00							
							(0.01)							
GED									0.02	0.11***				
									(0.11)	(0.02)				
GED Squared									0.01					
									(0.02)					
Training (DOT)											0.03	0.03***		
											(0.03)	(0.01)		
Training (DOT) Squared											0.00			
											(0.00)			
Training (O*NET)													0.11***	0.05***
													(0.02)	(0.01)
Training (O*NET) Squared													-0.01***	
													(0.00)	
Constant	1.99***	-0.07	-0.09***	0.01	-1.89***	-0.49***	-0.17	-0.21***	-0.09	-0.26***	0.09**	0.09***	0.00	0.06***
	(0.69)	(0.13)	(0.03)	(0.02)	(0.65)	(0.11)	(0.13)	(0.04)	(0.20)	(0.06)	(0.04)	(0.03)	(0.03)	(0.02)
Observations	322	322	322	322	322	322	321	321	322	322	322	322	322	322
R^2	0.06	0.02	0.43	0.37	0.37	0.33	0.38	0.38	0.32	0.32	0.14	0.14	0.38	0.32

Notes: Each column shows the coefficients estimated by OLS from the regression of 1980-2010 occupational mean log real wage changes on the corresponding skill measure shown in the rows. Wages, years of schooling and college share are computed from 1980 Census. See text for variable definitions. Regressions are weighted by occupations' 1980 employment share. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3.3: Predicting Occupational Skills with Wages

(Dependent Variable: Percentile Ranking of Occupational Skill Measures)

A. Lower Half of 1980 Wage Distribution

	College Shr.	Years of Sch.	AFQT	GED	Training (DOT)	Training (O*NET)
Wage Percentile Rank	-0.02	0.04	-0.05	0.14	0.38	0.18
	(0.19)	(0.20)	(0.17)	(0.22)	(0.25)	(0.17)
Constant	0.36***	0.34***	0.38***	0.30***	0.18***	0.29***
	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)
Observations	161	161	160	161	161	161
R^2	0.00	0.00	0.00	0.01	0.08	0.01

B. Upper Half of 1980 Wage Distribution

	College Shr.	Years of Sch.	AFQT	GED	Training (DOT)	Training (O*NET)
Wage Percentile Rank	0.65***	0.68***	0.67***	0.59***	0.86***	0.58***
	(0.21)	(0.19)	(0.17)	(0.15)	(0.14)	(0.18)
Constant	0.16	0.14	0.14	0.23*	0.01	0.25*
	(0.17)	(0.16)	(0.14)	(0.12)	(0.11)	(0.14)
Observations	161	161	161	161	161	161
R^2	0.11	0.13	0.14	0.14	0.22	0.12

Notes: Table shows the coefficients estimated by OLS from the regression of occupational percentile rank of corresponding skill measure in columns on percentile rank of average occupational wage in 1980. Panel A (B) shows the results for occupations below (above) the median of 1980 mean wage distribution. Wages, years of schooling and college share are computed from 1980 Census. See text for skill variable definitions. Regressions are weighted by 1980 employment share of occupations. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3.4: Predicting Occupational Skills with Tasks

(Dependent Variable: Percentile Ranking of Occupational Task Measures)

	Abstract	Manual	Routine	RTI	Time Demand	Cognitive Demand	Hazard
A. Lower Half of 1980 Wage Distribution							
Wage Percentile Rank	0.15	0.48	0.12	-0.46***	0.90***	0.57***	0.67***
	(0.25)	(0.34)	(0.15)	(0.34)	(0.17)	(0.16)	(0.18)
Constant	0.31***	0.36***	0.50***	0.70***	0.10***	0.23***	0.29***
	(0.05)	(0.10)	(0.10)	(0.04)	(0.04)	(0.05)	(0.06)
Observations	161	161	161	161	161	161	161
R^2	0.01	0.05	0.00	0.05	0.35	0.15	0.13
B. Upper Half of 1980 Wage Distribution							
	Abstract	Manual	Routine	RTI	Time Demand	Cognitive Demand	Hazard
Wage Percentile Rank	0.86***	-0.27	-0.56*	-0.53***	0.70***	0.84***	-0.56***
	(0.15)	(0.23)	(0.29)	(0.17)	(0.16)	(0.21)	(0.19)
Constant	0.07	0.68***	0.83***	0.77***	0.21*	0.02	0.90***
	(0.11)	(0.18)	(0.22)	(0.13)	(0.11)	(0.15)	(0.15)
Observations	161	161	161	161	161	161	161
R^2	0.24	0.02	0.05	0.05	0.19	0.18	0.06

Notes: Table shows the coefficients estimated by OLS from the regression of occupational percentile rank of corresponding task measure in columns on percentile rank of 1980 average occupational wage. Panel A (B) shows the results for occupations below (above) the median of 1980 mean wage distribution. Wages, years of schooling and college share are computed from 1980 Census. See text for task variable definitions. Regressions are weighted by 1980 employment share of occupations. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.B Figures

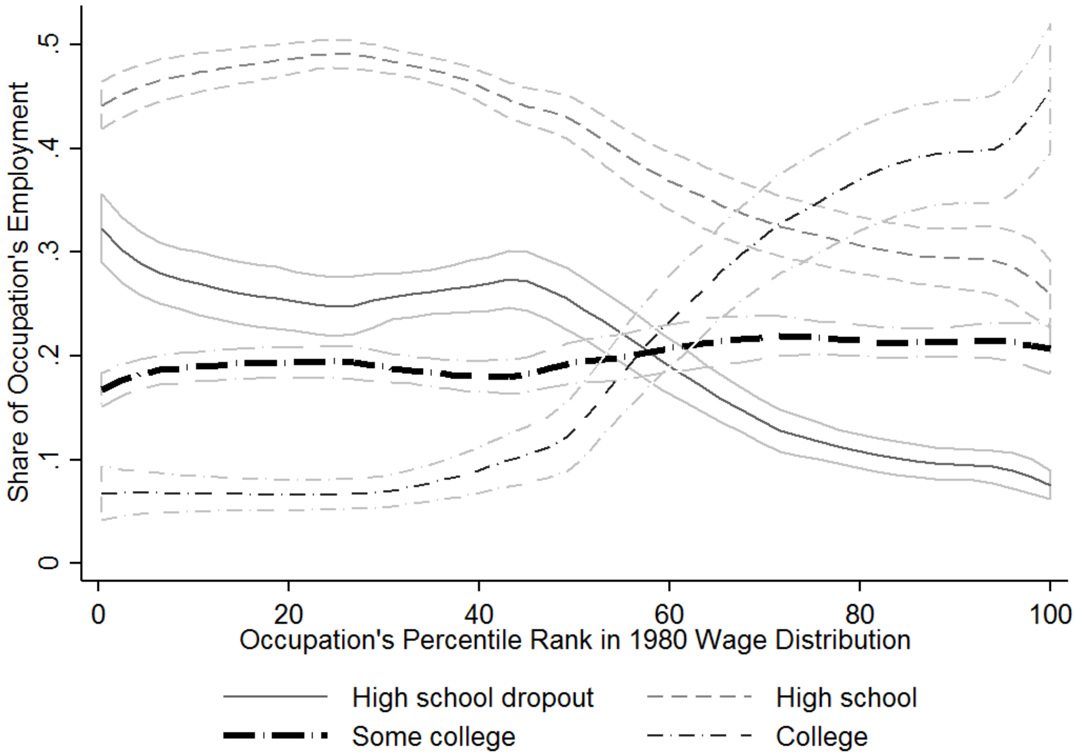

Figure 3.1: Occupational Skill Intensity and Wage Structure

Notes: Figure shows smoothed shares of each skill group in occupations' employment in 1980 by the 1980 occupational mean wage percentile rank. Smoothing is based on 322 consistent occupation codes following Dorn (2009)'s classification and performed by local polynomials of degree 0 with bandwidth of 10 and weighted by 1980 occupational employment shares. Employment shares and mean wages are calculated using labor supply weights in 1980 Census, that is Census weight times total annual hours worked for each individual. Smoothed points may not sum up to one since smoothing is done separately for each skill-group.

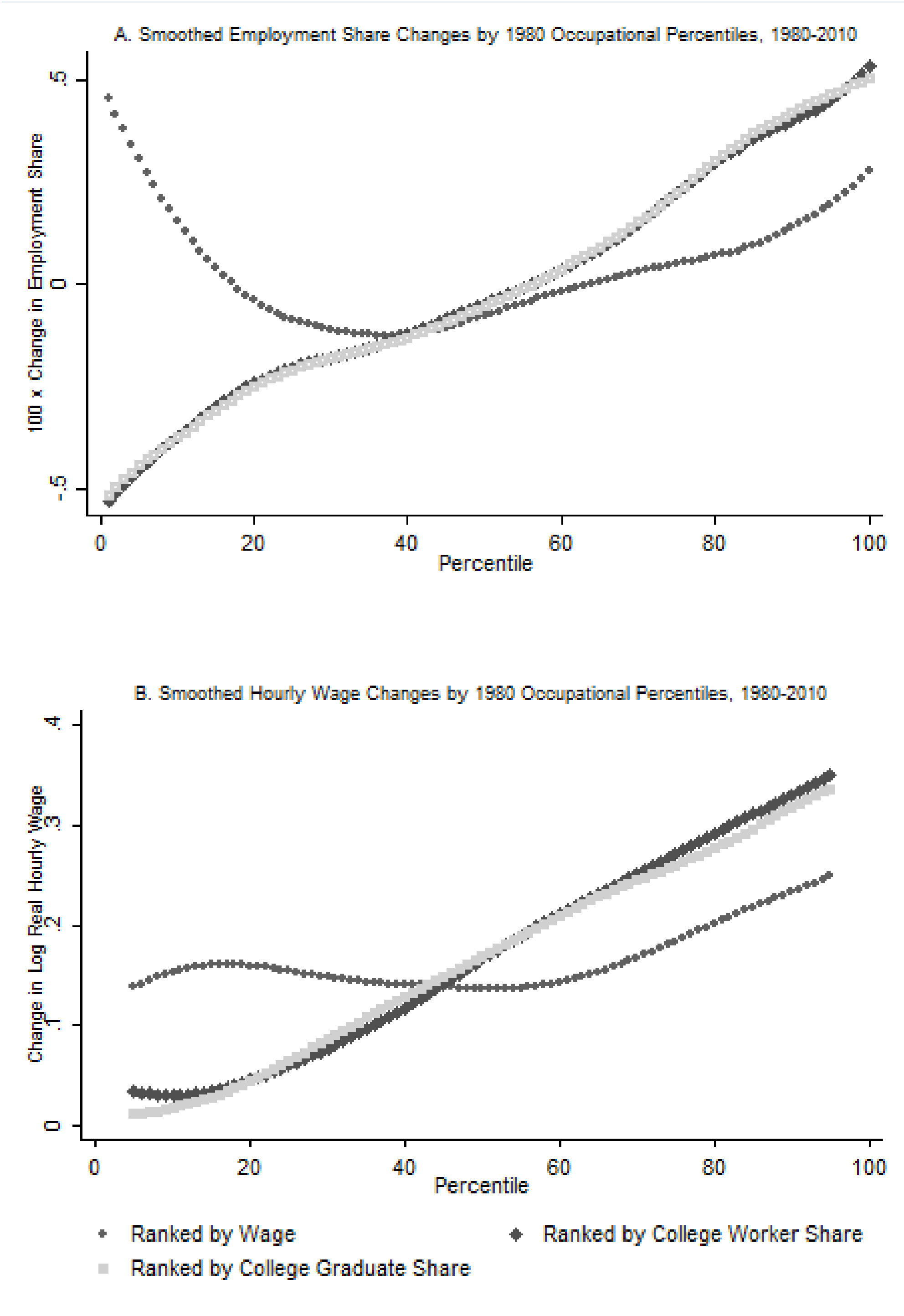

Figure 3.2: Change in Occupational Employment Share and Log Real Wages by Wage and Skill Percentiles

Notes: Figure shows smoothed 1980-2010 changes in occupational employment shares and mean log real wages computed for each employment percentile ranked according to 1980 occupational mean high-skill worker intensity or wages of 322 consistent non-farm occupations following Dorn (2009)'s classification. Construction of employment percentiles, computation of mean wages in each percentile and smoothing procedure follows Autor and Dorn (2013). The data comes from 1980 Census and 2010 American Community Survey. College worker share is the ratio of annual hours by workers with at least some college education in occupation's total labor supply. College graduate share is the ratio of annual hours by workers with at least a college degree in occupation's total labor supply. Real wages are calculated as total labor income divided by total hours and adjusted using personal consumption expenditure index. Labor supply weights are used in the computation of education and wages at occupation level.

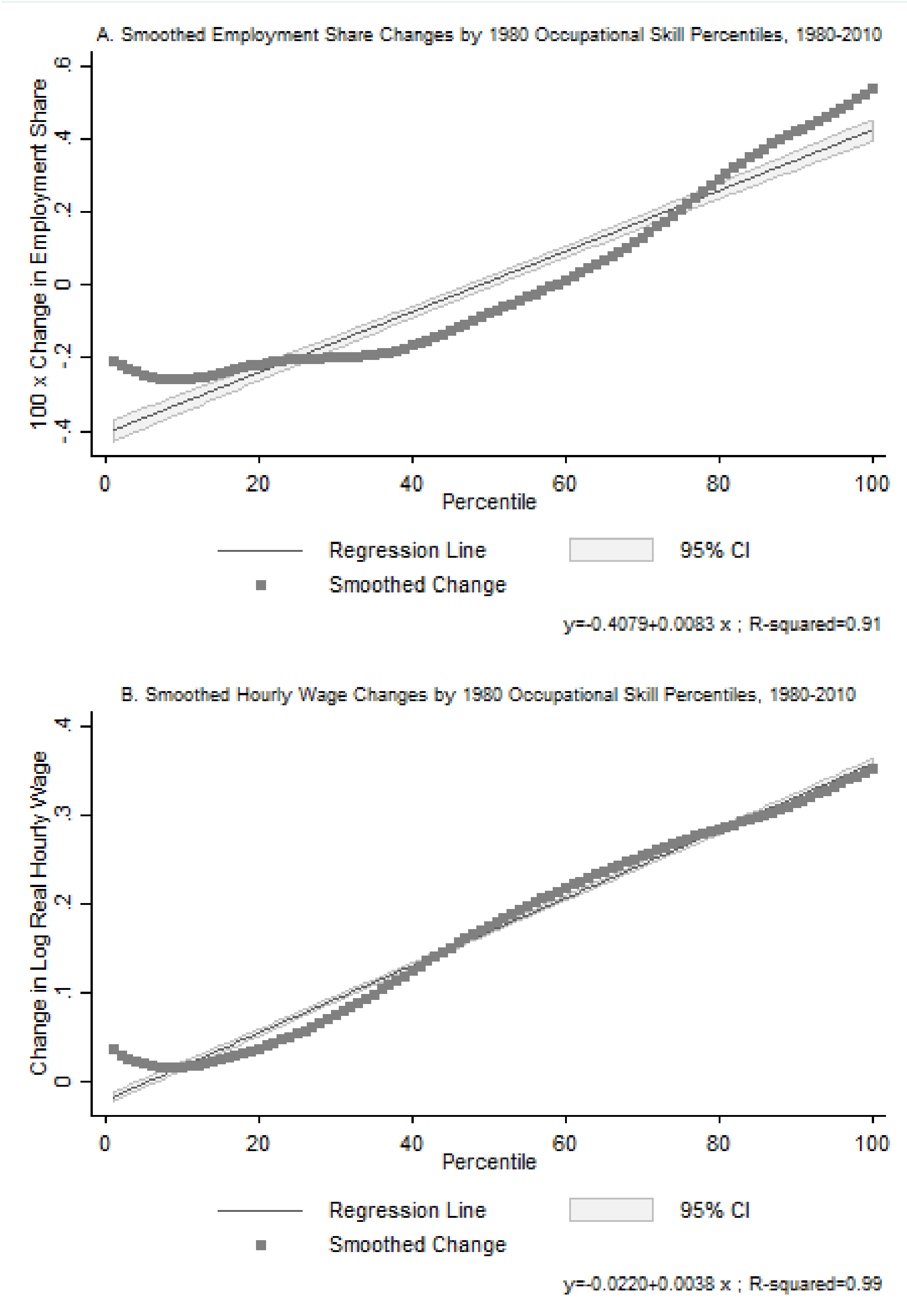

Figure 3.3: Occupational Employment Share Change and Real Wage Growth by Mean Years of Education

Notes: The figure shows smoothed 1980-2010 changes in occupational employment share and log real wages of occupations ranked by 1980 occupational mean years of education. The gray colored squares represent the smoothed points. The solid line represents the linear fit of smoothed points with 95 percent confidence interval indicated as shaded areas. The equation shows the OLS coefficients and R^2 from the regression of smoothed points on skill percentiles. For all other details see Figure 2 notes.

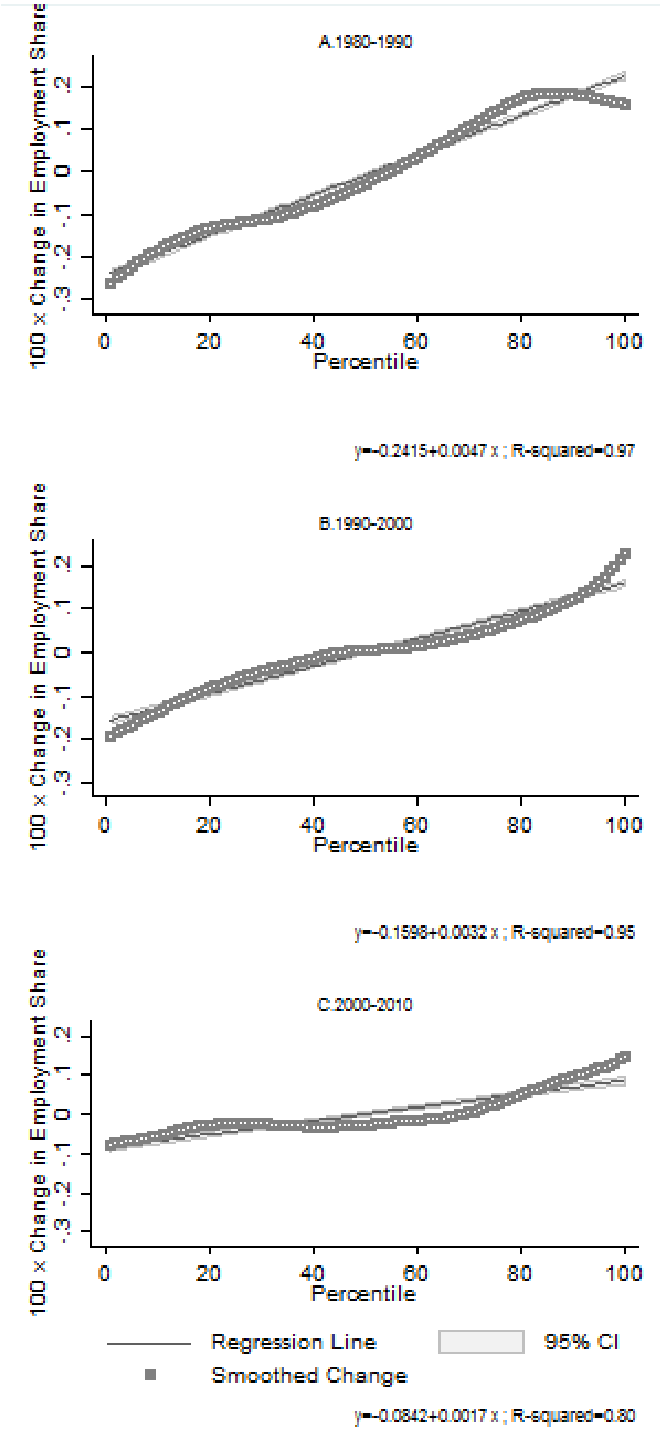

Figure 3.4: Decadal Changes in Occupational Employment Share by Skill

Notes: The figure shows smoothed 1980-1990, 1990-2000, and 2000-2010 changes in occupational employment share of occupations ranked by 1980 share of college workers in occupations' employment. The gray colored squares represent the smoothed points. The solid line represents the linear fit of smoothed points with 95 percent confidence interval indicated as shaded areas. The equation shows the OLS coefficients and R^2 from the regression of smoothed points on skill percentiles. For all other details see Figure 2 notes.

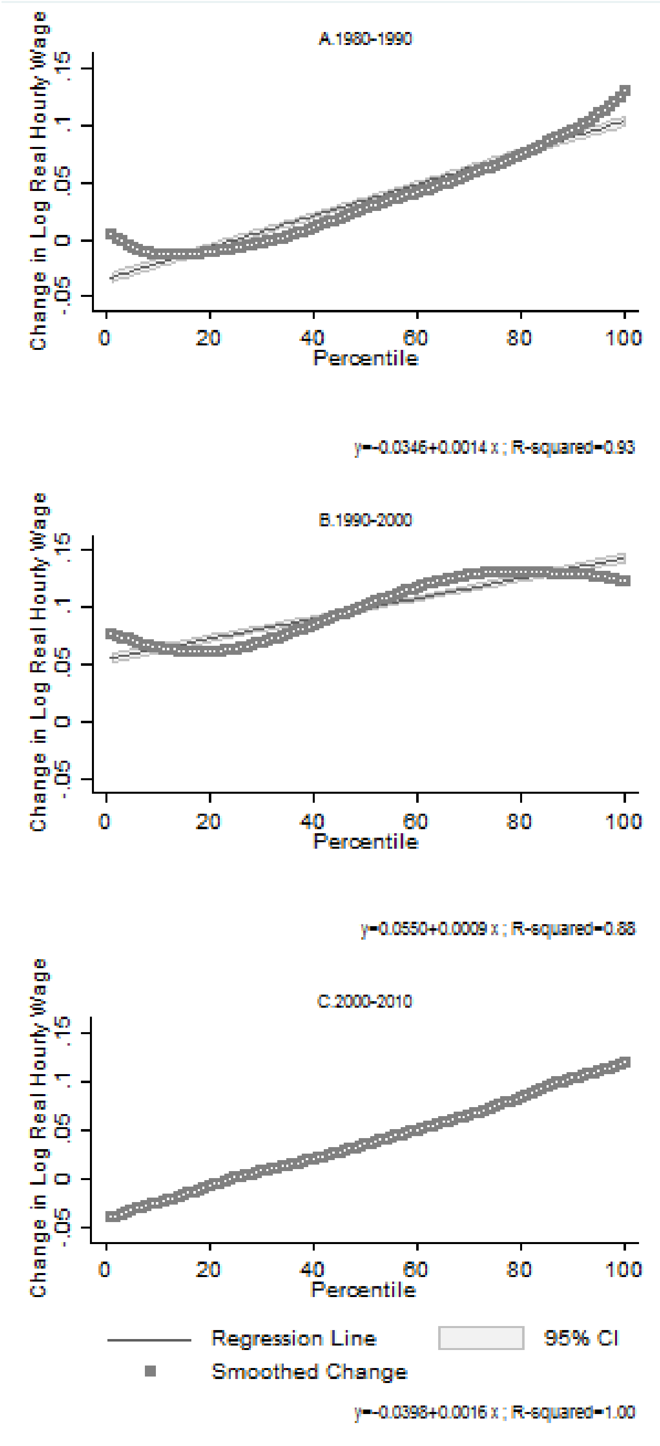

Figure 3.5: Decadal Changes in Occupational Real Wage by Skill

Notes: The figure shows smoothed 1980-1990, 1990-2000, and 2000-2010 changes in occupational mean log real wages of occupations ranked by 1980 share of college workers in occupations' employment. The gray colored squares represent the smoothed points. The solid line represents the linear fit of smoothed points with 95 percent confidence interval indicated as shaded areas. The equation shows the OLS coefficients and R^2 from the regression of smoothed points on skill percentiles. For all other details see Figure 2 notes.

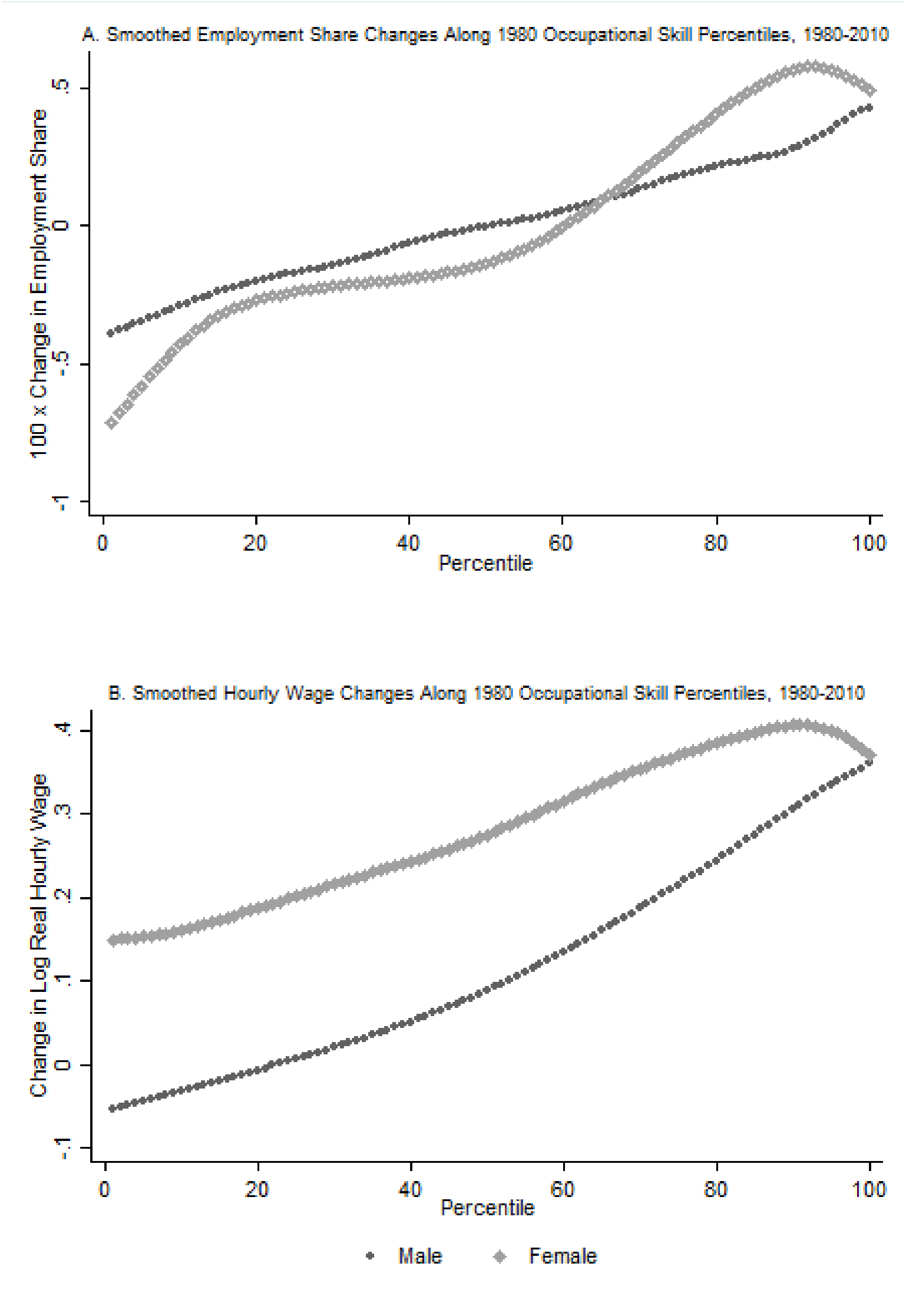

Figure 3.6: Monotonic Occupation Growth by Gender

Notes: The figure shows smoothed 1980-2010 changes in occupational employment shares and mean log real wages of occupations ranked by 1980 share of college workers in occupations' employment separately by labor markets of males and females. For all other details see Figure 2 notes.

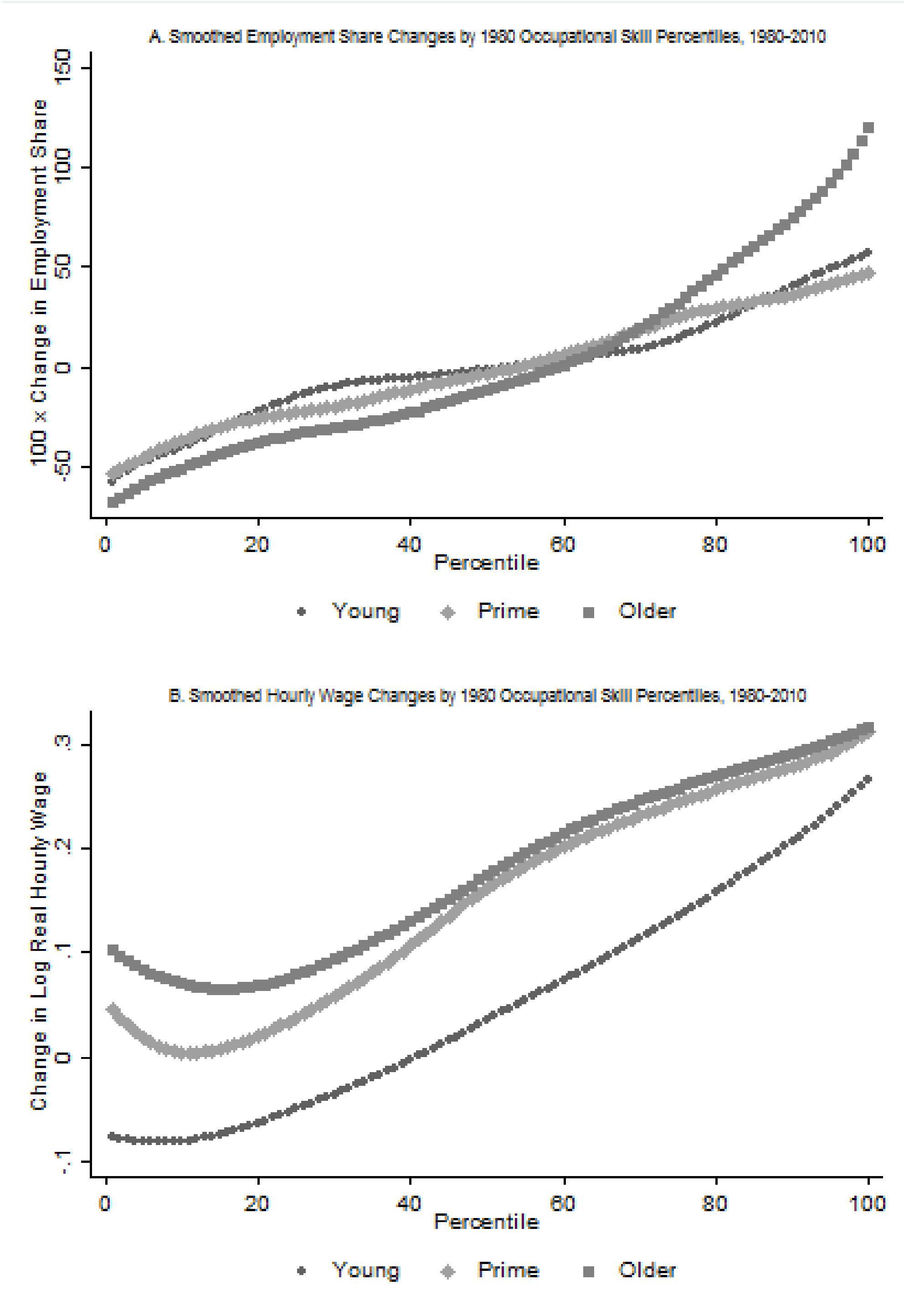

Figure 3.7: Monotonic Occupation Growth by Age

Notes: The figure shows smoothed 1980-2010 changes in occupational employment shares and mean log real wages of occupations ranked by 1980 share of college workers in occupations' employment separately by labor markets of age groups. Young, prime, and older groups correspond to workers of age 16-29, 30-54, and 55-64. For all other details see Figure 2 notes.

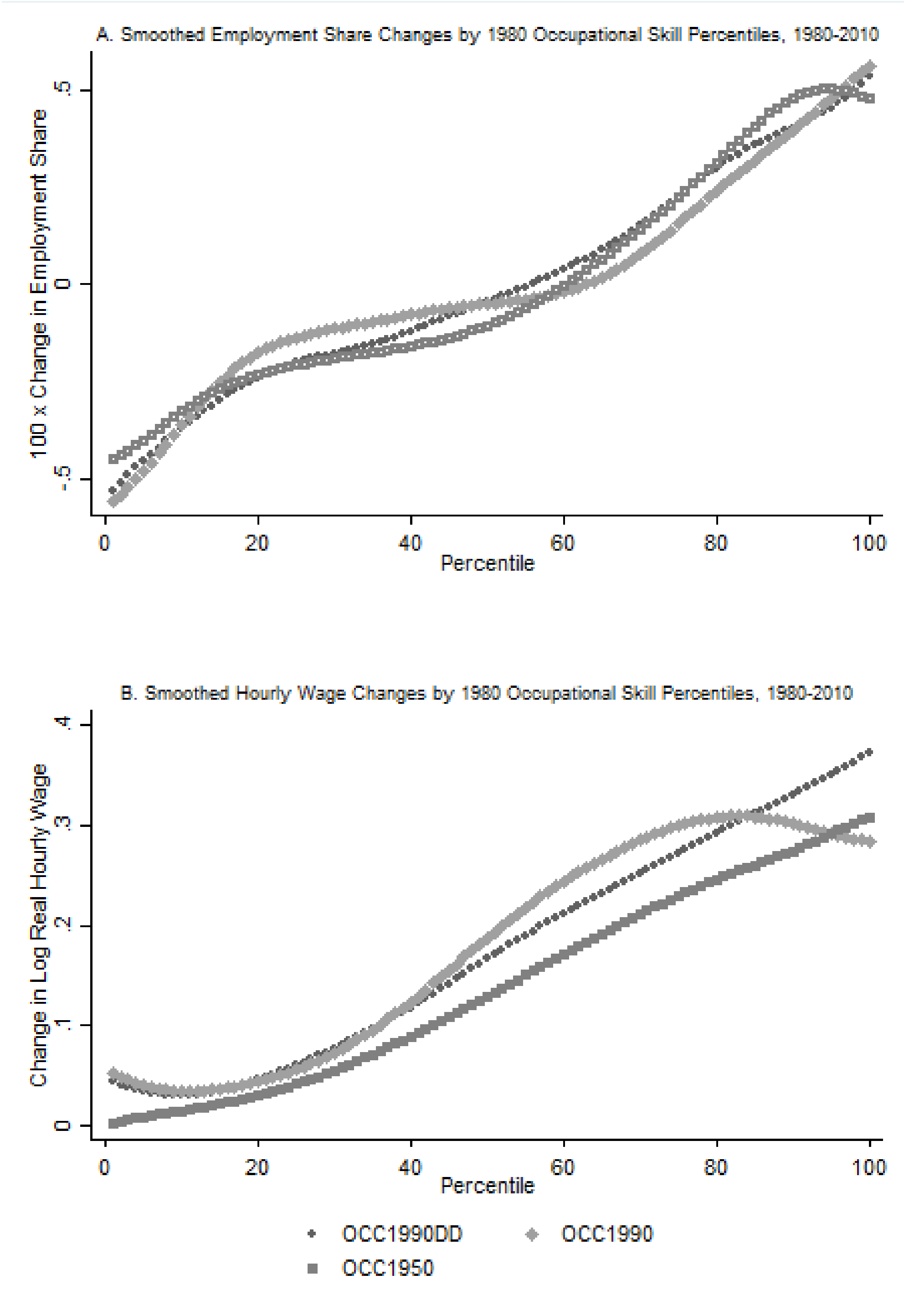

Figure 3.8: Monotonic Occupation Growth and Occupation Classification

Notes: The figure shows smoothed 1980-2010 changes in occupational employment shares and real log wages of occupations ranked by 1980 share of college workers in occupations' employment according to different occupation codes. See text for details on occupation codes. For all other details see Figure 2 notes.

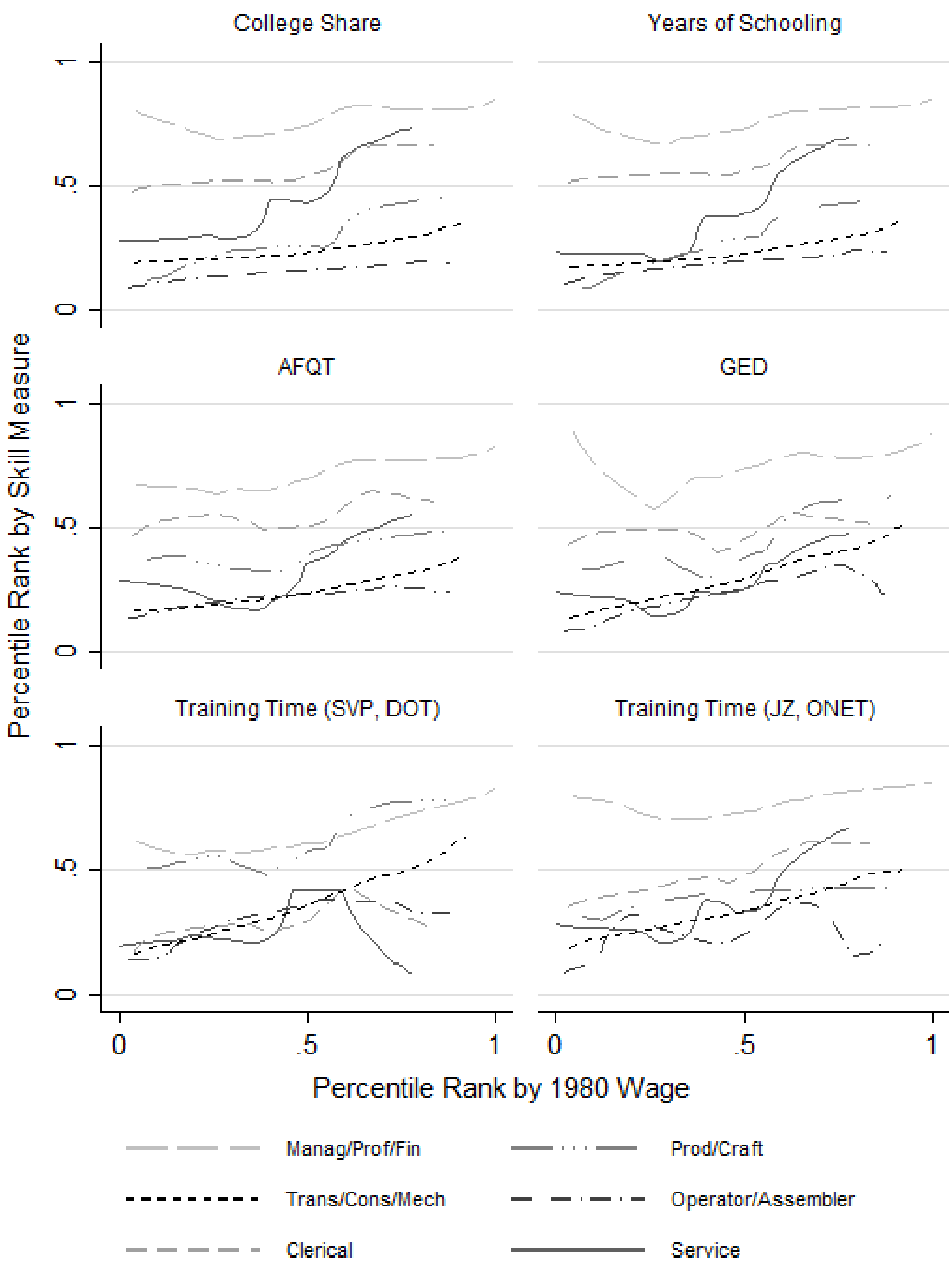

Figure 3.9: Skills and Wages by Occupation Group

Notes: The figure shows smoothed 1980 occupational mean skill intensity measures by occupations' 1980 mean wage percentile ranks (from 0 to 1) for major occupation groups. Smoothing is performed by local polynomials and weighted by occupations' employment shares. See text for details on skill variables.

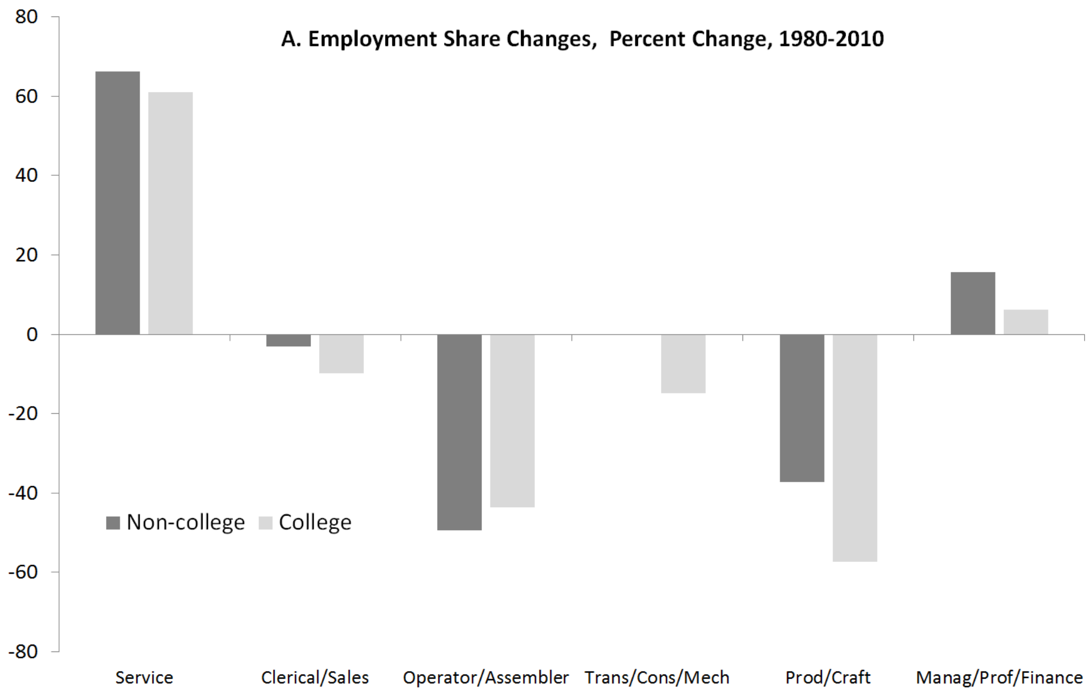

Figure 3.10: Polarization of College and Non-college Employment

Notes: The figure shows percentage change in employment share of major occupation groups separately by college and non-college workers. Occupation groups are ordered from left to right according to 1980 mean wages.

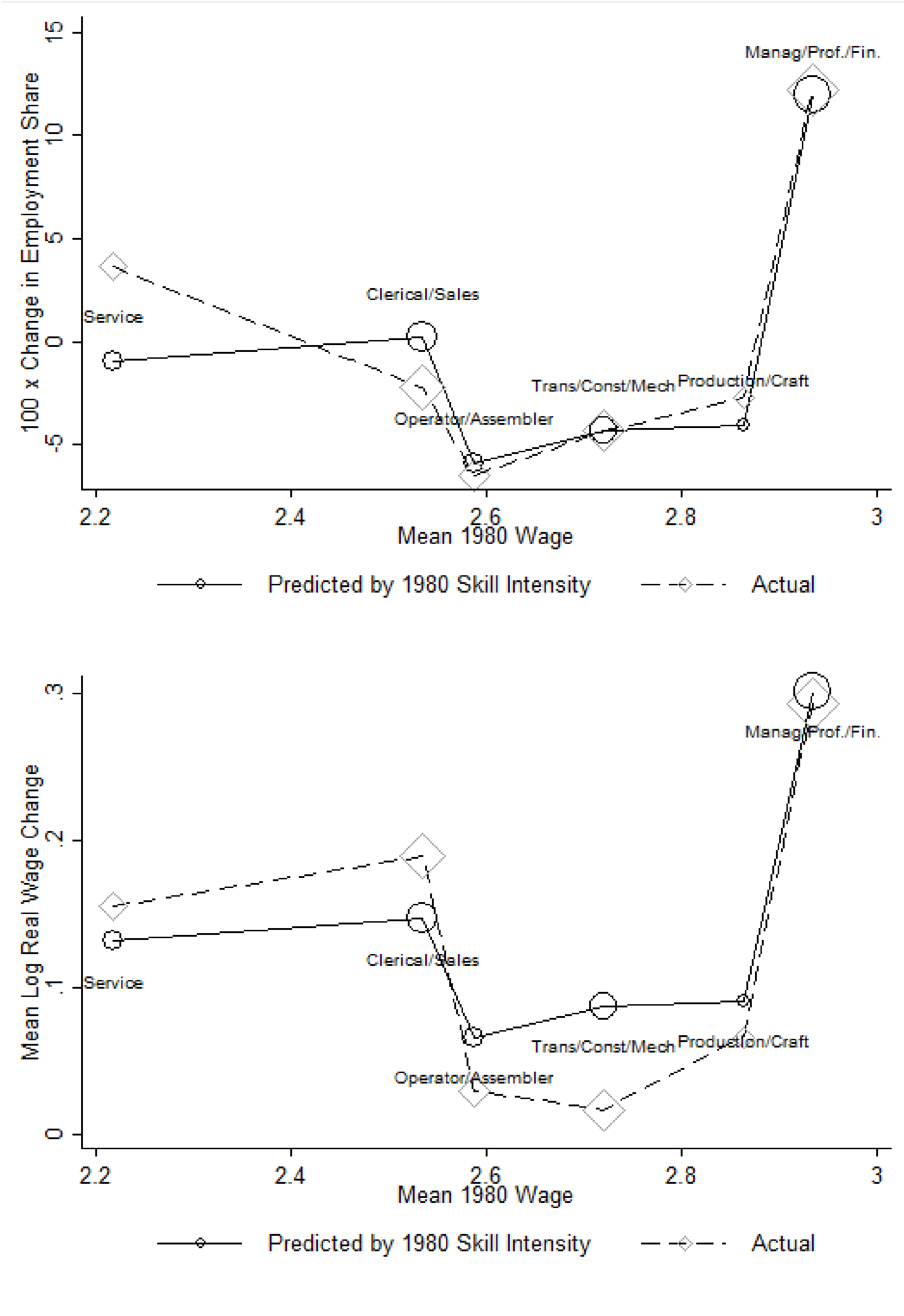

Figure 3.11: Actual and Predicted Employment Share Change and Wage Growth, 1980-2010

Notes: The figure shows actual and predicted employment share and mean log real wage changes by major occupations. Predicted changes are obtained by regressing the actual changes on the occupation group's skill intensity proxied by the college worker share of the median occupation in that group.

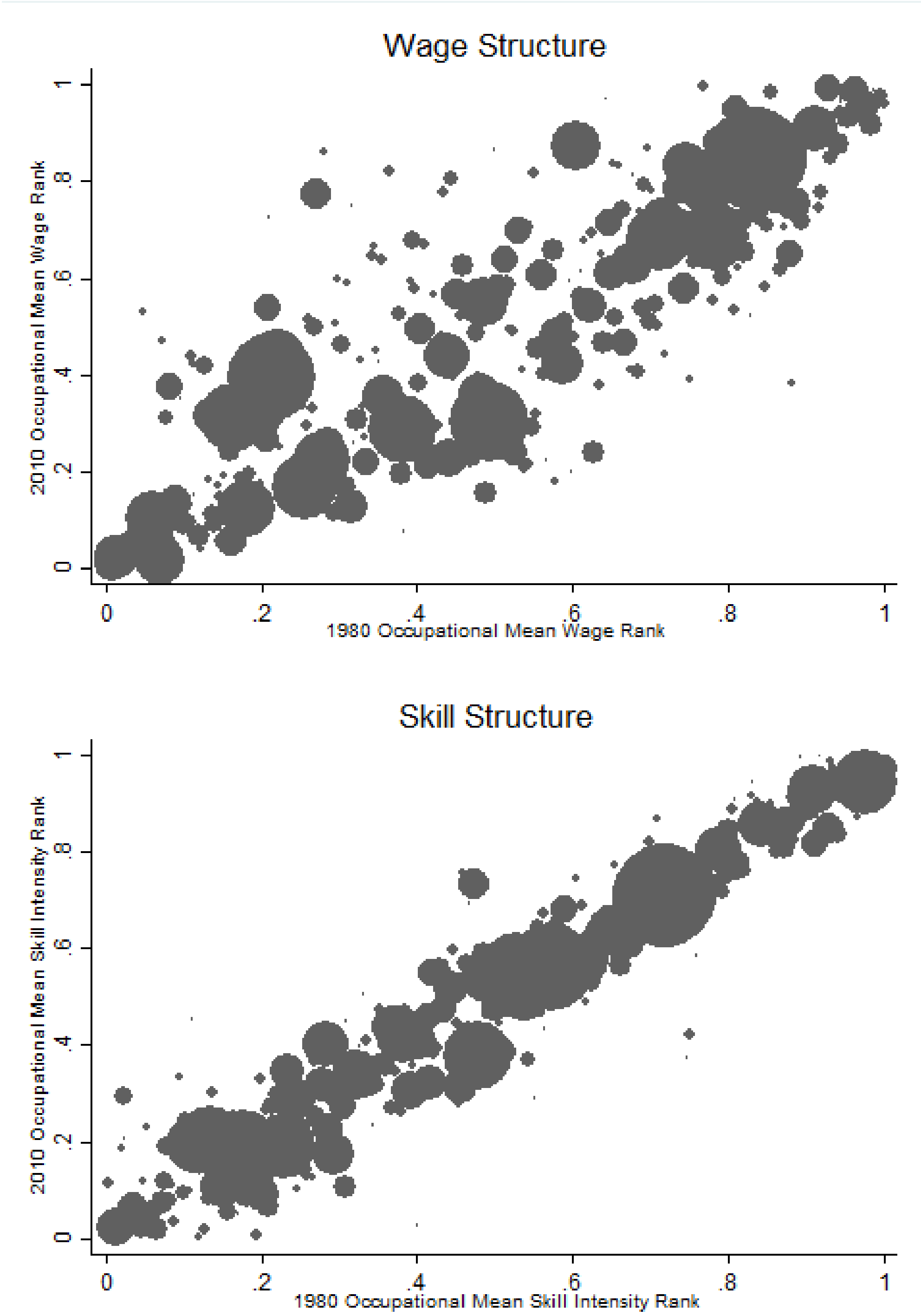

Figure 3.A.1: Wage and Skill Structure in the Long Run, 1980-2010

Notes: The figure compares 1980 and 2010 wage and skill rankings of occupations. Mean wage ranks are calculated as the percentile rank of real mean log wages, and mean skill intensity rank is calculated as the percentile rank of mean college employment share. The size of each point is proportional to corresponding occupation's employment share.

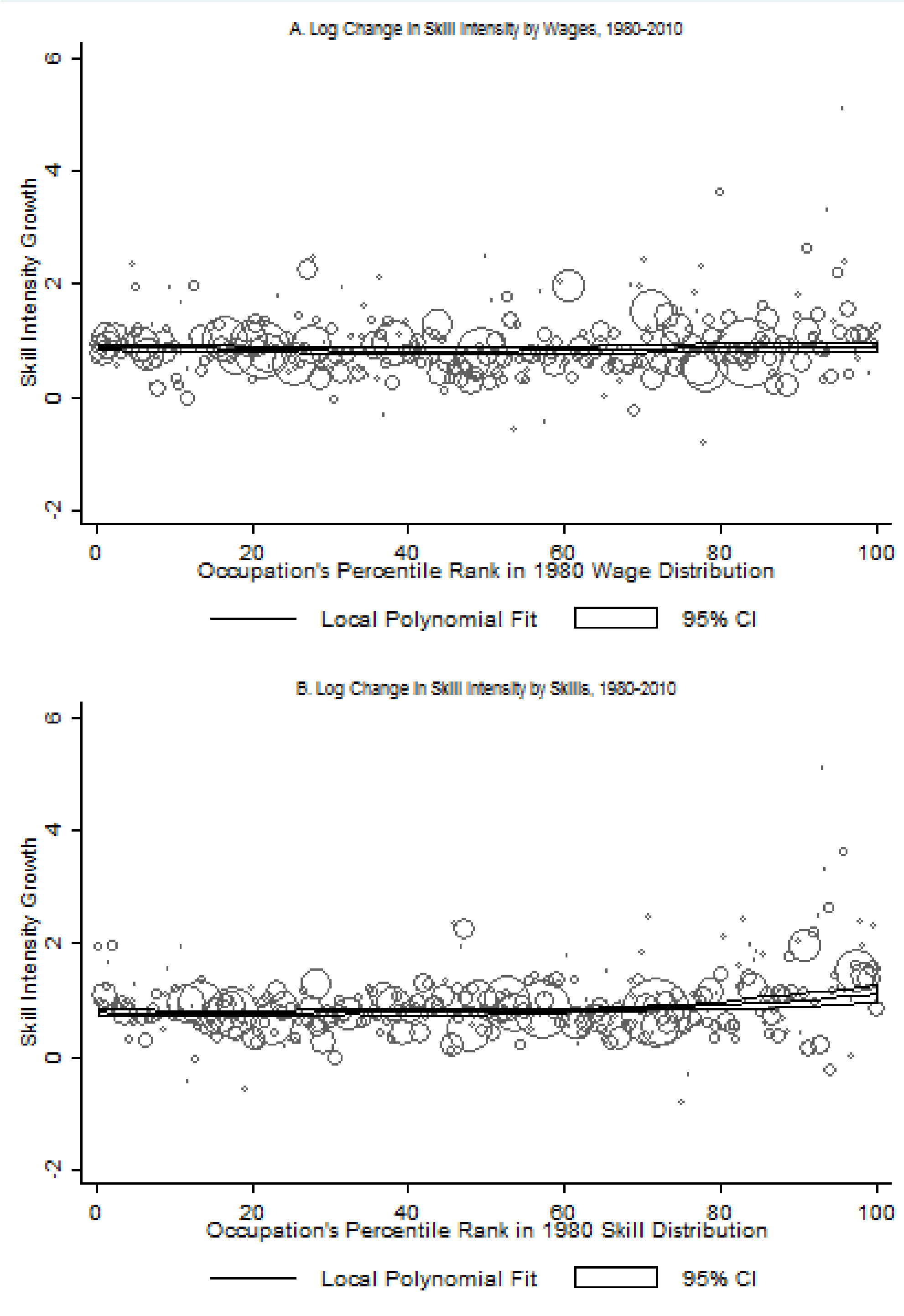

Figure 3.A.2: Change in Skill Intensity, 1980-2010

Notes: The figure plots 1980-2010 change in the log of skill intensity by initial wages (Panel A) and initial skill intensity (Panel B). Skill intensity is defined as annual hours worked by college workers divided by annual hours worked by non-college workers in each occupation. Circle size is proportional to the employment share in 1980. Solid lines inside boxes show the smoothed mean relationship by a local polynomial using labor supply weight, surrounded by 95% confidence interval.

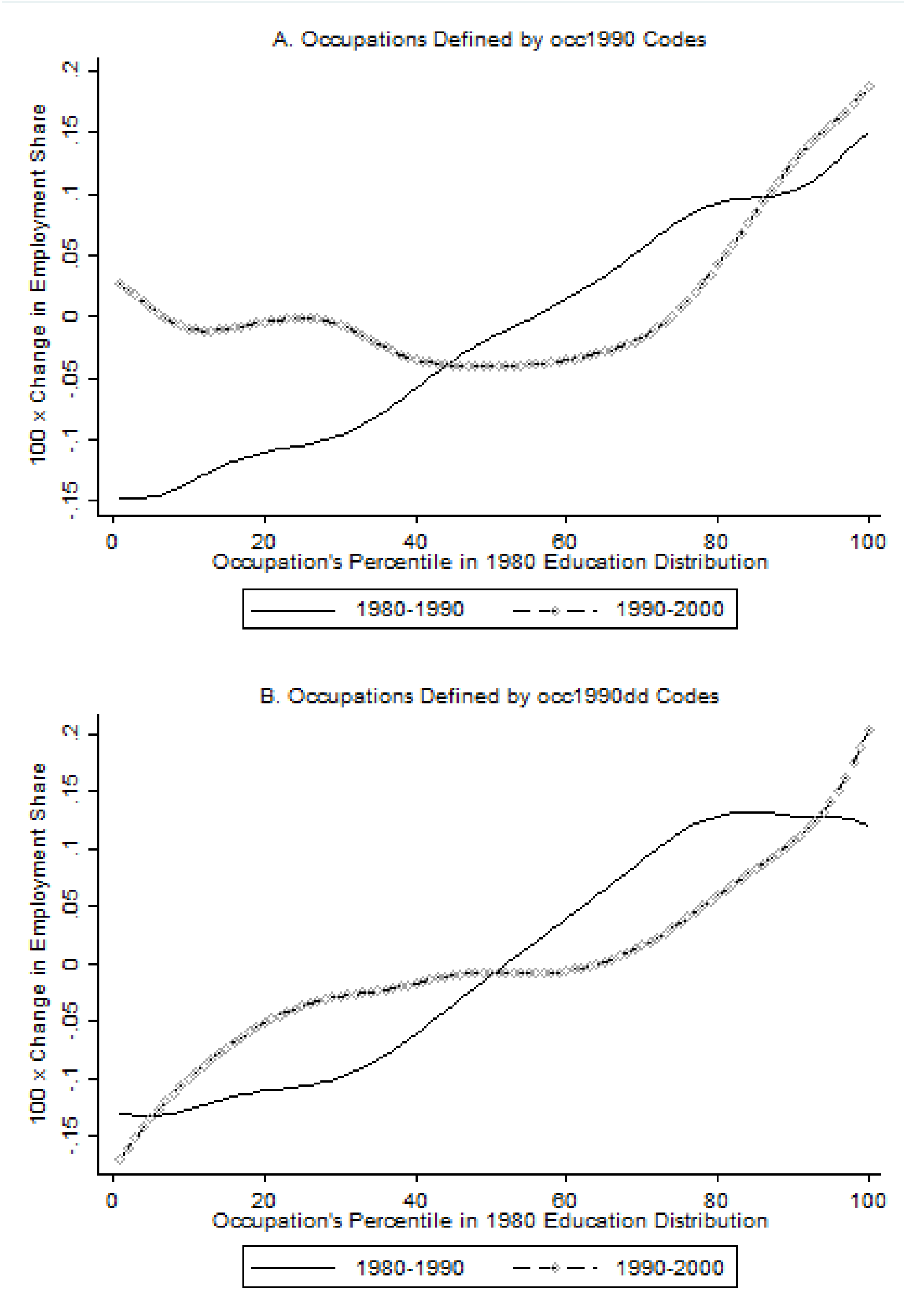

Figure 3.A.3: Smoothed Changes in Employment Share by Skill Percentile and Occupation Codes

Notes: Figure shows smoothed 1980-1990, and 1990-2000 employment share changes in occupational employment percentiles using the two occupation code system. Percentiles are ordered by occupational mean years of education in 1980. The data and smoothing procedure follows Autor, Katz, and Kearney (2008). *occ1990dd* occupation codes are merged to the original data by a crosswalk from Autor and Dorn (2013).

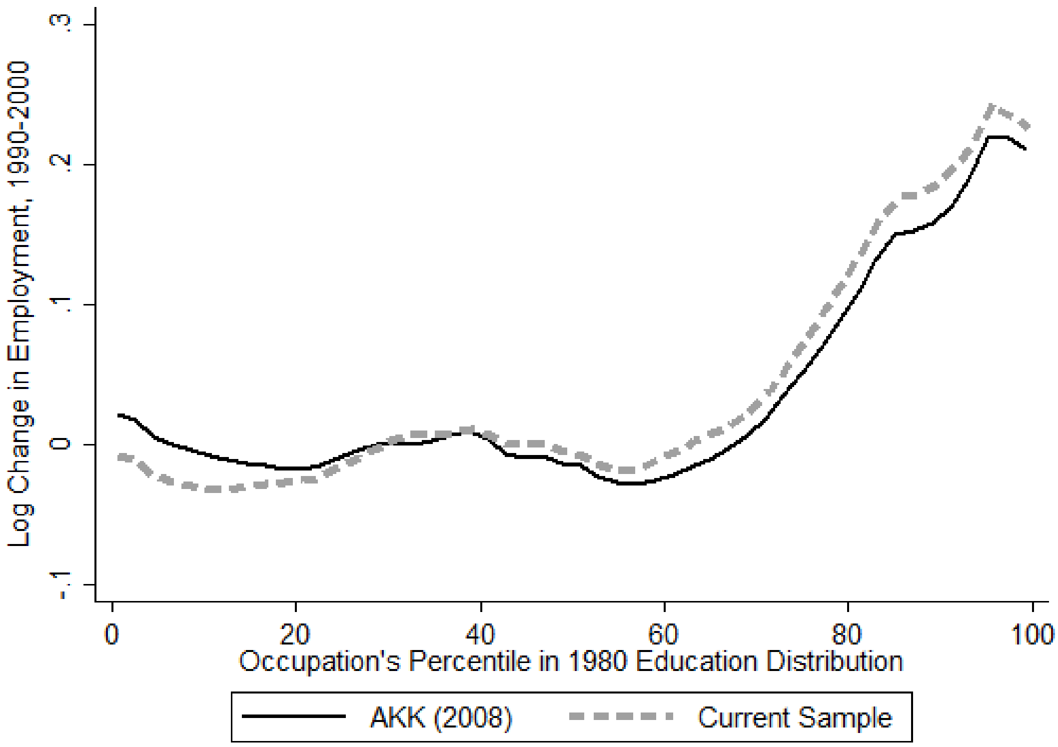

Figure 3.A.4: Smoothed Occupational Employment Growth of *occ1990* Occupations

Notes: Figure shows smoothed 1990-2000 employment growth by occupational employment percentile ranks using *occ1990* codes. Percentile ranks are based on occupational mean years of education in 1980. The smoothing is done by local polynomial smoothing with bandwidth 10 and weighted by 1980 employment. AKK(2008) indicates that the data used is Autor, Katz, and Kearney (2008). Current sample indicates the data used in this paper.

3.C Occupational Employment Growth in 1990s

Although the main indicator for job polarization in the literature is occupational employment changes by occupations' wage percentiles, there are two influential papers (Autor, Katz, and Kearney, 2008; Autor, Katz, and Kearney, 2006) in the literature that report non-monotonic employment changes along occupational mean education, particularly between 1990 and 2000. Since these findings seem to contrast with my observation on monotonic demand growth along the skill distribution, it is important to explore the source of difference between this paper and others. Therefore I provide a discussion on results of earlier papers here. I approach to untangle the set of puzzling results by directly using data released in David Autor's web page on Autor, Katz, and Kearney (2008).

The main practical difference between my paper and the two papers documenting polarization along education percentiles is the occupational classification. Autor, Katz, and Kearney (2008) use *occ1990* while this paper employs *occ1990dd*. As discussed in the main text the two coding schemes lead to similar observations of employment changes in the long-run, but this might not be the case in smaller frames of time. In order to be certain that occupation coding preference is the true source of divergence, next I report the results of the following data exercise. Autor, Katz, and Kearney (2008) provide their dataset including both *occ1990* and original Census codes *occ* in 1980, 1990, and 2000. Merging these *occ* codes to *occ1990dd* from the crosswalk provided by David Dorn, I redo the analysis in Autor, Katz, and Kearney (2008) on the basis of *occ1990dd* instead of *occ1990*.

Figure 3.A.3 shows the smoothed employment share changes according to two different occupation codes. The upper panel replicates corresponding Autor, Katz, and Kearney (2006) and Autor, Katz, and Kearney (2008) that shows smoothed 1980-1990 and 1990-2000 changes by means years of education percentiles where occupations are in *occ1990* codes. The lower panel shows the same with *occ1990dd* codes. The comparison between two shows that the particular trend in occupational employment growth during 1990s depends on occupation definitions.[25]

Considering that *occ1990dd* is an improved version of *occ1990*, and that in the long-run two codes lead to similar patterns of employment demand changes as I show

25 As shown in Section 3, however, the long run monotonicity of demand growth is not classification-specific.

in section 2, the striking contrast may seem puzzling. For this reason, I compare two coding schemes based on their stability of occupation coverage in Autor, Katz, and Kearney (2008)'s data. *occ1990dd* have 330 number of occupations with non-zero employment share in 1980, 1990, and 2000. There is little change in terms of representation of occupations. On the contrary *occ1990* reports 381 occupations in 1980, 380 in 1990 while there is only 336 in 2000. The difference between 1980 and 2000 coverage corresponds to around 3 percent of 1980 employment. The instability of *occ1990* might lead to inconsistency in terms of comparison of employment between 1980 and 2000 since each percentile is assumed to contain 1 percent of employment. Therefore percentiles formed according to employment shares can be misleading when using *occ1990*.

Finally, I check whether *occ1990* based figures imply polarization when a simpler method is used. Instead of forming percentiles of employment using employment shares I directly generate percentile rank of occupations by education. Also, since employment shares suffer from occupational inconsistency under *occ1990*, I directly use occupational employment growth. Figure 3.A.4 shows smoothed log change of 1990-2000 employment sorted by education percentiles in 1980. In order to see how my own sample compares with theirs I do the exercise both with Autor, Katz, and Kearney (2008) data and with the one used in this paper. Although it is true that *occ1990* codes do not indicate a sharp monotonic rise in 1990s when sorted by mean years of education, the resulting pattern surely does not imply polarization. The observation is also confirmed by the smoothed line from my data using *occ1990* and the same method, which suggests that differences between the observations of Autor, Katz, and Kearney (2006) or Autor, Katz, and Kearney (2008), and mine do not stem from sample or methodological differences.

In summary, the previous literature's direct evidence on employment polarization by education is not robust to the occupation codes used. Particularly, from 1990 to 2000 the coverage of *occ1990* significantly shrinks which makes smoothed graphs based on employment percentiles much less comparable between the periods. Hence *occ1990dd* used in later studies of labor market polarization (Autor and Dorn, 2013, e.g.,) provides a more reliable comparison which supports the monotonic employment growth by skill shares that is observed in this paper during each decade after 1980.

3.D Data Appendix

The data sources and variables are described in Section 2. In this appendix section I describe the details on Census samples used in the paper. The Census data cover 1980, 1990, 2000 Census 5% extracts, 2005 and 2010 surveys of ACS. The sample includes workers of age 16-64, employed workers excluding armed forces and self-employed who reported positive wage income. Employment of an occupation is total annual hours worked computed as usual weekly hours times weeks worked variables. Labor supply weights are calculated as annual hours times population weights. Wage bill of an occupation is defined as total annual wage income. Wage income is subject to top-code treatment such that top-coded observations are multiplied by 1.5. Real wages are computed in terms of 2010 dollars and the adjustment is done by PCE index. Real hourly wages are computed as real annual wage income divided by annual hours. For each sample year I assign real hourly wages smaller than the first percentile of wage distribution equal to the first percentile's real hourly wage.

3.E Theory Appendix

In this appendix section I show the existence and uniqueness of the equilibrium solution of the model and provide the proof of the claims in proposition 1. The case with $J = 3$ is sufficient to prove all parts of the proposition. Therefore without loss of generality I study the economy with three occupations. Generalizing the proof for $J > 3$ number of occupations is straightforward. First, I show that there exists a unique equilibrium allocation of labor across occupations in the model. Secondly, I show that under the assumptions in proposition, the occupations' employment growth is proportional to β_j. Then, I show that occupational mean wage growth is monotonically increasing in β_j. Lastly, for the labor market polarization result I construct a case which illustrates that polarization of employment and wages can be obtained as the model's outcome.

Before the proof of the proposition, I first show the existence of the unique equilibrium in terms of employment allocations of each skill type across occupations. Combining the first order conditions for optimal task choice, and optimal skill type demand the following can be derived for relative share of employment of skill-type H in two arbitrarily chosen occupations j and j':

$$\left(\frac{h_{jt}}{h_{j't}}\right)^{(1-\rho)} = \left(\frac{d_{j'}\gamma_j}{d_j\gamma_{j't}}\right)\left(\frac{\beta_j}{\beta_{j't}}\right)^{(1-\rho)}\left(\frac{1-\beta_j}{1-\beta_{j't}}\right)^{\frac{\rho-\mu}{\mu}} \left(\frac{\left(\frac{\beta_j}{1-\beta_j}\right)\left(\frac{\beta_{j't}}{1-\beta_{j't}}\right)^{-\mu}\left(\frac{H_{j't}}{L_{j't}}\right)^{\mu}\left(\frac{A_{Ht}}{A_{Lt}}\right)^{\mu}+1}{\left(\frac{\beta_{j't}}{1-\beta_{j't}}\right)\left(\frac{\beta_{j't}}{1-\beta_{j't}}\right)^{-\mu}\left(\frac{H_{j't}}{L_{j't}}\right)^{\mu}\left(\frac{A_{Ht}}{A_{Lt}}\right)^{\mu}+1}\right)^{\frac{\rho-\mu}{\mu}}, \tag{3.55}$$

where $s_{jt} = \frac{S_{jt}}{S_t}$ for $S = H, L$ denotes the employment share within the skill group.

The resource constraint on employment together with equation (3.53) implies the following for the ratio of high-skill worker to low-skill in occupation j:

$$\frac{H_{jt}}{L_{jt}} = \frac{H_t}{L_t}\left(a_{jj'} + (1-a_{jj'})\, h_{jt} + (a_{ji} - a_{jj'})\, h_{it}\right), \tag{3.56}$$

where $a_{mn} = \frac{\beta_m(1-\beta_n)}{\beta_n(1-\beta_m)}$ for two occupation index number m and n; and j, j', i denote the three occupations.[26]

In order to characterize the equilibrium allocation, I plug (3.56) into (3.55) and express h_{1t} as a function of h_{2t} from the comparison of occupations indexed as 1 and 3:

$$h_{1t} = (1-h_{1t}-h_{2t})\left(\frac{d_3\gamma_1}{d_1\gamma_3}\right)^{\frac{1}{(1-\rho)}}\left(\frac{\beta_1}{\beta_3}\right)\left(\frac{1-\beta_1}{1-\beta_3}\right)^{\frac{\rho-\mu}{\mu(1-\rho)}} \left(\frac{\left(\frac{\beta_1}{1-\beta_1}\right)\left(\frac{\beta_3}{1-\beta_3}\right)^{-\mu}\left(\frac{H_t}{L_t}a_{31}\left(a_{13}+(1-a_{13})\,h_{1t}+(a_{12}-a_{13})\,h_{2t}\right)\right)^{\mu}\left(\frac{A_{Ht}}{A_{Lt}}\right)^{\mu}+1}{\left(\frac{\beta_3}{1-\beta_3}\right)\left(\frac{\beta_3}{1-\beta_3}\right)^{-\mu}\left(\frac{H_t}{L_t}a_{31}\left(a_{13}+(1-a_{13})\,h_{1t}+(a_{12}-a_{13})\,h_{2t}\right)\right)^{\mu}\left(\frac{A_{Ht}}{A_{Lt}}\right)^{\mu}+1}\right)^{\frac{\rho-\mu}{\mu(1-\rho)}}.$$

Let's assume that $\beta_1 > \beta_2 > \beta_3$. From the equation it can be verified that $h_{2t} = 1$ implies $h_{1t} = 0$; and $h_{2t} = 0$ implies $0 < h_{1t} < 1$. In this relation h_{1t} can be found as the intersection of 45 degree line representing the left hand side and the curve given by the right hand side, treating h_{2t} as exogenous. The left hand side is increasing in h_{1t} and independent of h_{2t}. The right hand side is decreasing in both h_{1t} and h_{2t} since it is assumed that $0 < \mu < \rho < 1$. Therefore, a higher h_{2t} is a downward

26 Note that given relative skill supply in an occupation, relative skill supply for any other occupation can be obtained simply by equation (3.53).

shift of the right hand side and leads to a lower value for h_{1t}. Consequently, h_{1t} is monotonically decreasing in h_{2t} while $0 < h_{2t} < 1$.

In the same way, h_{2t} can be written as a function of h_{1t} from the comparison of occupations indexed as 2 and 3. By symmetry, $h_{1t} = 1$ implies $h_{2t} = 0$; $h_{1t} = 0$ implies $0 < h_{2t} < 1$; and h_{2t} is strictly decreasing in h_{1t}. The relations described in this and previous paragraph has a single intersection point within the assumed range of employment shares. Therefore there exists only one pair of (h_{1t}, h_{2t}) that satisfies both equations. Since h_{3t} is given by h_{1t} and h_{2t}, and l_{1t}, l_{2t}, l_{3t} can be uniquely obtained using (3.56), within the unit square there exists a unique equilibrium allocation. Here the assumption on the ordering of the βs is not restrictive, for any other ordering the same argument holds after suitable adjustments in the occupation sub-indexes.

Now I move to proving that rising relative technology for high-skill workers implies reallocation of labor into more skill intensive occupations. Let's keep assuming that $\beta_1 > \beta_2 > \beta_3$. Then it follows that $a_{13} > a_{12} > 1$. First, consider the alternative case that $\frac{A_{Ht}}{A_{Lt}}$ rises and $\frac{h_{1t}}{h_{2t}}$ falls. By symmetry of (3.55), $\frac{h_{2t}}{h_{3t}}$ decreases too. From (3.56) it is clear that $\frac{H_{1t}}{L_{1t}}$ increases which, together with skill-biased technology growth, (3.55) implies that $\frac{h_{1t}}{h_{2t}}$ increases, contradicting the constructed case. Similarly, consider the other alternative that $\frac{h_{1t}}{h_{2t}}$ does not change following the change in technology. By symmetry, $\frac{h_{2t}}{h_{3t}}$ is fixed too. As a result $\frac{H_{1t}}{L_{1t}}$ is constant, and (3.55) implies a rising $\frac{h_{1t}}{h_{2t}}$, which is a contradiction. Therefore the new unique equilibrium allocation is consistent only with reallocation of high-skill labor into more skill intensive occupations, i.e., those with higher β. Equation (3.53) suggests that the same holds for low-skill employment. Hence, occupational employment growth and consequently employment share change is an increasing function of β_j.

The relative occupational mean wages at equilibrium can be shown in the following representation for two arbitrarily chosen occupations j and j':

$$\frac{w_{jt}}{w_{j't}} = \left[\frac{d_j}{d_{j'}}\right] \left[\frac{\left(\frac{H_{j't}}{L_{j't}}\right)+1}{a_{jj'}\left(\frac{H_{j't}}{L_{j't}}\right)+1}\right] \left[\frac{a_{jj'}\left(\frac{\beta_{j'}}{1-\beta_{j'}}\right)^{1-\mu}\left(\frac{H_{j't}}{L_{j't}}\right)^{\mu}\left(\frac{A_{Ht}}{A_{Lt}}\right)^{\mu}+1}{\left(\frac{\beta_{j'}}{1-\beta_{j'}}\right)^{1-\mu}\left(\frac{H_{j't}}{L_{j't}}\right)^{\mu}\left(\frac{A_{Ht}}{A_{Lt}}\right)^{\mu}+1}\right] \tag{3.57}$$

The part of the proposition on wage growth follows from the equation. The right-hand side of the equation is strictly increasing when $\beta_j > \beta_{j'}$ because second and third brackets increase when there is skill-biased technology growth. The term in the second bracket rises since $\frac{H_{j't}}{L_{j't}}$ falls and $a_{jj'} > 1$.[27] The last term in the brackets is also increasing since the numerator grows faster than denominator ($a_{jj'} > 1$).[28]

I end the proof by constructing a wage structure that enables employment and wage polarization along occupational wages. Since the relative employment and wage growth is entirely determined by the relative skill intensity, the construction aims to put the lowest β_j occupation in the middle of the wage ranking. I construct the case such that $\beta_2 < \beta_1 = \beta_3$. Then the desired wage structure is obtained if $w_{1t} > w_{2t} > w_{3t}$. This is possibly the case for $d_1 > d_2 > d_3$ where d_1 is sufficiently large and d_3 is sufficiently low. Inspecting equation (3.57) for $j = 2$ and $j' = 1$ indicates that the last two term in brackets on the right-hand side are both bounded. The second term in brackets converge to 1 as the skill intensity goes to zero from above. The last term in brackets converges to a_{21}.[29] Hence, there exists d_1 high enough to ensure $w_{2t}/w_{1t} < 1$ for given time t. Similarly, inspecting equation (3.57) for $j = 2$ and $j' = 3$ shows that the last two term in brackets on the right-hand side are both bounded, and converge to 1 and a_{23}, respectively. Hence, there exists d_3 low enough to ensure $w_{2t}/w_{3t} > 1$ for given time t.

□

27 This follows (3.56) as a result of the reallocation of high-skill workers towards more skill intensive occupations.

28 Note that growth of $\frac{A_{Ht}}{A_{Lt}}$ implies growth of $\frac{H_{j't}A_{Ht}}{L_{j't}A_{Lt}}$ in equilibrium for any occupation j'. This is given by the first part of the proposition and equation (3.55).

29 This can be derived by applying L'Hôpital's rule while $\frac{H_{j't}A_{Ht}}{L_{j't}A_{Lt}}$ goes to infinity.

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