Interpersonal-Service Tasks and the Change in the US Employment Structure*

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Abstract

This paper takes a task-based perspective on the growth of service occupations and sectors. I document that the key task aspect characterizing service sector specialization of occupations is interpersonal interactions with customers (interpersonal-service tasks) and that 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 interacts with technical change in a way that is different from computer adoption. I reconcile the empirical facts in a model of occupation-based structural change with two distinct channels of technology where interpersonal-service task intensity of occupations is linked to higher task-specific technology adjustment costs, and routinizability leads to deepening of computer capital. While the model can successfully predict employment reallocation across detailed occupations and industries, growth accounting of employment based on estimation of the model suggests a leading role for interpersonal-service tasks in jointly explaining job polarization and service sector growth in the US.

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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. This paper aims to develop the task content that is at the heart of structural shifts into service employment at both the sector and occupation level, characterize its connections with technical change, and quantifies its impact on employment reallocation.

I start with developing a task measure for direct customer interactions which focuses on work context and activities rather than worker skills and abilities. 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. In the terminology of this paper interpersonal-service tasks exclude service provision without interpersonal interactions, and interactions without service content.[4] The set of jobs with the highest inerpersonal-service task intensity 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. In Section 2 of this paper I show

[1] Herrendorf et al. (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 et al. (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] Here the service content is defined according to the existence of an actual customer. The index measures the importance of interpersonal interactions with customers and not the complexity of the interactions. 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.

that interpersonal-service task intensity is (i) able to successfully predict service-specialization of occupations, (ii) unrelated to cognitive skills while reflecting non-cognitive skills well, (iii) essentially distinct from interpersonal interactions within the firm (iv) not part of routine-biased technical change as it is not significantly correlated with the intensity of computerization.

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 who 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 et al., 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 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 relative 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 computerization 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]

Building on these insights, I introduce in Section 3 a model of structural change at the task level that predicts the empirical facts on interpersonal-service tasks. In a framework involving several industries and occupations, I model interpersonal-service task intensity as an adjustment cost of the technology adoption in a certain task. Consequently, occupation-specific technology growth is decreasing in interpersonal-service task intensity. 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.[7]

I evaluate the quantitative performance of the model in Section 4. Following the estimation strategy of Goos et al. (2014) and using employment and industry data for the US between 1987 and 2014, I estimate the employment equation 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.

[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] 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.

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 employment growth under sector-occupation structure allows for disentangling task-specific demand shifters from sectoral ones.[8] Estimations applying 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 sizeable impact on employment reallocation 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[9], 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 et al., 2006, 2008).

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 literature.[10] Borghans et al. (2008b) 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. Borghans et al. (2014) develop a comprehensive interpersonal measure by combining *people* tasks from DOT to understand the impact of technology on the labor market outcomes of

[8]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.

[9]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 et al. (2014) extend the idea so that occupations effectively face different declines in the price of capital input proportional to their routinizability.

[10]See Borghans et al. (2008a) for a review.

underrepresented groups. Postel-Vinay and Lise (2015) study multidimensional skills in relation to human capital and using a comprehensive approach classify the tasks in three as cognitive, manual, and interpersonal. One of their findings is that interpersonal task aspect is a distinct productive attribute in the labor market. A fundamental departure of my paper from those papers is that I solely focus on task heterogeneity of occupations 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.

The paper is closely related to the literature on tasks which assigns a key role to routinization in driving changes in occupational employment (e.g., Autor et al., 2003, 2006; Goos et al., 2009; Acemoglu and Autor, 2011; Autor and Dorn, 2013; Goos et al., 2014). Results of this paper suggest a milder long-run impact of routinization on between-occupation reallocation of employment. This paper also differs by locating interpersonal-service tasks distinctly from within-firm interactions which are closely related to interpersonal task elements of the routine-biased technical change framework.[11]

This paper is also connected to the recent papers that link sectoral and occupational employment trends. Barány and Siegel (2017) argue that polarization of jobs and wages in the US is driven by structural change at the sector level. In contrast, I conclude that both the growth of service sector growth and job polarization is to a large extent accounted for by the task-based sources.[12] In this sense, the paper is related to Duernecker and Herrendorf (2017) who build a model of structural change featuring a binary service classification of sectors and occupations where slower technology growth in service occupations drive both sectoral and occupational shifts. I extend their analysis to a continuous measure of service activity at the task level and further allow to differentiate from routine-biased technical change.

In another related work Lee and Shin (2017) study an economy with occupation-sector structure in the labor market and assess the impact of task-specific technical change. They argue that faster productivity growth in middle-wage occupations not only drives polarization but also capable of explaining the structural change. Task-specific technical change that they back out have the highest correlation with non-routine interpersonal task intensity. While the authors interpret the importance of interpersonal tasks within the routinization framework, their results are in line with this paper's

[11] Autor et al. (2003) introduce non-routine interpersonal tasks that stresses the importance of direction, control, and planning of work organization. Deming (2015) argues that starting with the 2000s the social skills have been increasingly more important in the labor market and builds a model that stresses the cooperation and coordination among co-workers in the production process.

[12] Bárány and Siegel (2018) also find that bulk of the employment reallocation is due to occupation-based sources without using data on task intensities.

nuanced view of automation.

2 Interpersonal-Service Tasks

2.1 The Measure and Distinctive Characteristics

In untangling the service-relevant task content, interpersonal-service task intensity (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 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 follows the content model which provides a rich and detailed set of occupational characteristics. The database includes a set of occupational content categories each containing 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.*

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. 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.[13] Next, I calculate the mean across related task variables to calculate the two indexes for each occupation group, which is once 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. On the other hand, the conceptual differences between the two interpersonal task variables can be easily confirmed by cross-occupation comparisons of the measures.

Occupations that have the highest ITI scores are jobs in health, education, social work and clergy, sales, and personal services.[14] The most interpersonal-service intensive occupations seem to be homogeneously specialized in the service sector whereas they display great diversity in terms of skills. Lowest ITI scorers are mostly manual tasks without interpersonal content. Many of them are more likely to be located in the goods producing industries while high-skill workers such as computer programmers also exist.

Within-firm interactions suggest contrasting patterns when compared to interpersonal-service tasks. Top of the within-firm interactions ranking are dominated by high-skilled jobs rich in management and supervisory content. The bottom is mostly characterized by low-skilled manual task intensive jobs. In addition both top and bottom of the list involves a lot of typical service sector jobs, suggesting a weak association between within-firm interaction intensity and sectoral specialization.

Guided by the comparisons of top and bottom interpersonal-service and within-firm interactive occupations, next I formally test how both measures differ in terms of reflecting service-activity and

[13]See data appendix for initial steps of task variable construction.
[14]Table B.1 provides the list of top and bottom 15 jobs for the two interaction measures.

skills using direct measures in Table 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.

The strategy used in developing the interpersonal measures employs the task content information in O*NET. A natural question is then how the interpersonal task contents are related to interpersonal or other type of skills. Online Appendix Table 3 shows the partial correlations of interpersonal task measures with various skills from the Dictionary of Occupational Titles (DOT).[15] The table reports that ITI is not significantly related to cognitive skills measured by intelligence aptitute, data complexity and creative preference. It is also unrelated to direction, control and planning (DCP) variable which is the cognitive interpersonal skill measure of Autor et al. (2003). The last four rows of Table 3 uses the non-cognitive interpersonal skill measures from the DOT.[16] Despite the weak association with cognitive skill measures, ITI seems highly correlated to non-cognitive skill measures. On the other hand, within-firm interactions are closely connected to both cognitive and non-cognitive skill measures with the exception of "influencing people".

As a measure of service content involving interpersonal customer interactions interpersonal-service tasks form a distinct task aspect compared to the existing task approaches in the literature. It is

[15] 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.

[16] These are "dealing with people beyond instructions", "talking", "people complexity", "influencing people".

essentially different from within-firm interactions, which is closely related to cognitive-interpersonal tasks of Autor et al. (2003) and social skill measure of cooperation and coordination in the production process by (Deming, 2015). It is also distinct from other aspects of task classification based on routinization or offshoring perspective. First, it is different from non-routine manual tasks as many of manual-intensive jobs do not require intense interactions with the customers. It is also different from routine and offshorable tasks since many activities scoring high in interpersonal-service tasks are open to be computerized or replaced by workers in foreign markets, such as sales and customer support jobs.[17]

2.2 The Changing Task Demand

Interpersonal-service task content both conceptually and empirically, captures the key aspects of service production in the labor market. Considering the continuous rise of service employment it can be expected that employment is attracted to jobs with higher interpersonal-service intensity. In the following, 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 interpersonal-service task intensity in the relative employment growth of occupations in the long run.

The first evidence regarding shifting task demand towards interpersonal tasks is provided by Figure 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 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 non-monotonic courses. The continuous 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,

[17] Empirical evidence on the differences of interpersonal-service tasks and other task aspects are provided in Online Appendix B.1.

[18] This approach follows Autor et al. (2003) which is then used by others (e.g., Borghans et al., 2014; Deming, 2015).

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 (Blinder and Krueger, 2013; Autor and Dorn, 2013; Goos et al., 2014).[19]

Though the visual evidence from Figure 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 2 on the long-run stability of task shifts towards ITI, I use 1980-2010 changes in occupational employment indicators from Census and ACS and run the following regressions:

$$\Delta e_j = c + \sum_{x \in X} \beta_y^x x_j + u_j, \tag{1}$$

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

Estimated OLS coefficients of equation (1) when dependent variable is the log change in total hours are reported in Table 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

[19] Figure 2 suggests ITI and RTI as the two important task aspect regarding the changing occupational structure in the economy. In Online Appendix Section B.2 I dig deeper into the potential connection between ITI and RTI by performing the same analysis in Figure 2, this time comparing ITI and components of RTI index.

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 relative employment, 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 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 4, I include dummies for six major occupation groups that are listed in Table B.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.[20,21]

[20] Table 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. Table 5 confirms the key role of interpersonal-service tasks in the changing labor market importance of occupations in the long-run.

[21] Table B.4 provides evidence that ITI performs also superior also compared to within-firm interactions, which are closely correlated with social and cognitive skills. Controlling for the skill intensity of occupations leaves no predictive value for within-firm interactive task content as expected.

2.3 Interpersonal-Service Tasks and Technology

Interpersonal-service task intensity is a key metric for the service activity of continually growing importance in the labor market at the task level. For most analytical models, biased technical change is the fundamental force in the changing reallocation of employment. Most notably, the structural change literature attributes growing service employment to the goods-biased nature of technological change whereas at the task level the technology growth is routine-biased. If one assumes that sector employment is a collection of occupations then routine-biased technical change can potentially drive both occupational and sectoral reallocation of employment. Therefore how to interpret interpersonal-service tasks with respect to technical change emerges as an important question.

Given that routine-biased technical change is driven by widespread adoption of computer technologies, there are two potential cases that can sensibly address the growth of interpersonal-service tasks. In the first case, although interpersonal-service intensity and the existing measures of routinization are distinct, they are complementary measures of routine-biased technical change. The implication under this scenario is that the framework of Autor et al. (2003) should be improved by considering interpersonal-service tasks. This result is similar to how Goos et al. (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 channel. The second case is closer to how the structural change literature tends to view the service activity. In this view customers, who are crucial ingredients of the service output, make it hard to improve efficiency because of their preferences or skills.

The literature suggests a specific channel regarding how routinization leads to faster productivity growth. The mechanism of routine-biased technical change assigns a key role to capital, specifically to ICT capital. High routine task intensive occupations, industries, and economies go through greater levels of ICT intensification, or computerization (Autor et al., 2003; Autor and Dorn, 2013). If interpersonal-service tasks is part of routinization hypothesis then it should be directly linked to measures of computerization similar to the existing measures of routinization.

Following this line of reasoning I provide evidence on how ITI is related to adoption of computers 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 former provides occupational information on the importance of interactions with computers in the performance of the task. This variable reflects computerization but since it measures interactions only it might fail to capture computerization that took place without requiring intense worker-computer 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 6 reports the OLS estimation results from regression of the computerization measure on ITI, RTI and components of routinization framework.[22] The specification at Column (1) includes only ITI. The small and 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 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 et al. (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

[22] 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.

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 6 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 6 hold for more detailed occupation categories and more direct task variables Figure B.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 6, 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 7.[23] 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.

[23]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.

Last evidence on computerization and tasks comes from the US local labor markets in Table 8. 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 capital. Commuting Zones provide a natural geographic unit in terms of economic connections at the local level. In particular I estimate the following equation:

$$PC_{kst} = \delta_s + d_t + \sum_{x \in X} \beta_x x_{kst_0} + \epsilon_{kst}, \tag{2}$$

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.[24]

In Table 8 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 do not seem to be part of routine-biased technical change.[25]

Results of this section suggests that interpersonal-service task intensity affects employment

[24] 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.

[25] The relationship between productivity and task intensities is discussed in Online Appendix Section B.3. Online Appendix Table B.5 confirms that sectors with high ITI (RTI) exhibit higher labor productivity growth as expected.

reallocation most likely in the form of a friction on the growth of neutral technology, which is effective independent of worker skills and intensity of computer 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.

3 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 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 et al. (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 (Ngai and Pissarides, 2007; Acemoglu and Guerrieri, 2008). 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.

3.1 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

[26] Goos et al. (2014) do not study the general equilibrium model, but take into account demand effects in their empirical analysis.

of industries is I and total number of occupations is J. The production follows the following CES functional form:

$$Y_{it} = \left[\sum_{j}^{J} (\phi_{ij})^{\frac{1}{\theta}} (T_{ijt})^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}, \tag{3}$$

where $i = 1, \ldots, I$; $j = 1, \ldots, J$; 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 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:

$$\max_{T_{ijt}} \left[p_{it} Y_{it} - \sum_{j}^{J} \tau_{jt} T_{ijt} \right]. \tag{4}$$

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

$$T_{ijt} = \phi_{ijt} \left(\frac{p_{it}}{\tau_{jt}} \right)^{\theta} Y_{it}. \tag{5}$$

3.2 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:

$$T_{ijt} = A_{jt} L_{ijt}^{\alpha} E_{ijt}^{1-\alpha}, \tag{6}$$

where A_{jt} is occupation-specific technology term; L_{ijt} and E_{ijt} denote labor and task capital respectively for occupation j operating under industry i.

The occupation-specific technology term includes the economy wide technology A_t and the level

[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.

of technology adoption chosen by firms a_{jt} in the following form:

$$A_{jt} = \left(A_t a_{jt} - \frac{a_{jt}^{\rho_j}}{\rho_j} \right), \tag{7}$$

where $\rho_j > 1$ is the convex cost of technology adoption.

I assume that the occupation-specific neutral technology term is affected by the interpersonal-service task intensity. There is an economy-wide technology level in the economy, A_t, so that a rising tide of technology potentially lifts all boats (occupations) similarly. However, firms can choose how much of this new technology, e.g. know-how, management, or workplace practices, they would like to actually apply. In the context of customer-worker interactions, the presence of convex adjustment costs of adopting new technology generates a trade-off. On the one hand, the new technology is desirable because it increases output per effective input. On the other, it is introduced through a change in the way production process, hence part of the output is lost due to less efficient interactions with customers. This cost, captured by the convexity of technology adjustment ρ_j, will be a greater constraint when customers are more directly involved in the production process.

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:

$$E_{ijt} = \left(K_{ijt}^C \right)^{\kappa_j} \left(K_{ijt}^N \right)^{1-\kappa_j}, \tag{8}$$

where κ_j is the occupation-specific share of computers in task capital. I assume that a task's routinizability is given by the share of computing capital. Computing capital here refers to any equipment that performs or assists codifiable computing tasks.

Profit maximization problem of the task producer is as follows:

$$\max_{a_{ijt}, L_{ijt}, K_{ijt}^C, K_{ijt}^N} \left[\tau_{jt} T_{ijt} - w_{jt} L_{ijt} - p_t^C K_{ijt}^C - p_t^N K_{ijt}^N \right], \tag{9}$$

where w_j, p^C, p^N respectively denote wage rate, price of computing and other capital which firms take as given, and T_{ijt} is given by equations (6),(7), and (8).

Optimal level of technology adoption is given by the following first order condition for problem (9):

$$a_{ijt} = A_t^{\frac{1}{\rho_j - 1}}, \tag{10}$$

which simply implies that adoption is lower when the adjustment costs are higher.

Plugging (10) into (7)leads to the following equation for the occupation-specific technology:

$$A_{jt} = \left(\frac{\rho_j - 1}{\rho_j}\right)\left(A_t^{\frac{\rho_j}{\rho_j - 1}}\right). \tag{11}$$

Equation (11) shows that the the growth in occupation-specific technology becomes slower as the convexity of adoption costs increase, i.e., a lower ρ_j. The assumed form of technology adoption assures that the optimal adoption level is independent of the inputs of production. Labor- or capital-augmenting technical change does not have any effect on the degree of adoption the firm will choose. Therefore firms' profit maximization is identical to the case where A_{jt} as defined in equation (11) is exogenous.

In order to see key mechanism of routinization one can construct the ideal price index for aggregate task capital E_{ij}:

$$p_{jt}^E = \left(\frac{p_t^C}{p_t^N}\right)^{\kappa_j} p_t^N \Omega_j, \tag{12}$$

where $\Omega_j = \kappa_j^{-\kappa_j}(1-\kappa_j)^{-(1-\kappa_j)}$. Equation (12) implies that across occupations relative price of task capital depends on κ_j only. The price of task capital aggregate, p_j^E, 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:

$$\frac{p_t^C K_{ijt}^C}{p_{jt}^E E_{ijt}} = \kappa_j. \tag{13}$$

The demand for labor and the composit capital input is given by first order conditions of (9):

$$L_{ijt} = \frac{\alpha \tau_j T_{ijt}}{w_t} \tag{14}$$

$$E_{ijt} = \frac{(1-\alpha)\tau_{jt} T_{ijt}}{p^E_{jt}}, \tag{15}$$

where p^E_{jt} is defined as in equation (12).

3.3 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:

$$K_{t+1} = (1-\delta)K_t + Y_{Xt}, \tag{16}$$

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

[28]Price of the investment good is normalized to one.

perfectly competitive firms in each task capital sub-sector 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 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:

$$r = p_t^C B_t^C = p_t^N B_t^N \tag{17}$$

Equation (17) 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.

3.4 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:

$$\sum_{t=0}^{\infty} \beta^t \log C_t, \tag{18}$$

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:

$$\sum_i^I p_{it} C_{it} + K_{t+1} = (1 - \delta + r_t) K_t + w_t L_t. \tag{19}$$

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:

$$C_{it} = \lambda_i^{\epsilon-1} \left(\frac{p_{it}}{P_t}\right)^{-\epsilon} C_t, \tag{20}$$

where the price index, P, is given by

$$P_t = \left[\sum_i^I \left(\frac{p_{it}}{\lambda_i}\right)^{1-\epsilon}\right]^{\frac{1}{1-\epsilon}}. \tag{21}$$

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

$$\frac{P_{t+1}C_{t+1}}{P_t C_t} = \beta\left(1-\delta+r_t\right). \tag{22}$$

3.5 Equilibrium

At each time $t \geq 1$, given occupation-specific technology for each occupation $\{A_{jt}\}_{j=1}^J$, 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 $\{\tau_{jt}\}_{j=1}^J$, 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 $\left\{\{T_{ijt}\}_{j=1}^J\right\}_{i=1}^I$, 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 (18) subject to (19),
2. In each industry, firms maximize profits according to (4),
3. In each occupation of each industry, firms maximize profits according to (9),
4. As a result of competition and profit maximization (17) holds in the task-capital market, and $r_t = B_X$ holds in the investment sector,
5. Household capital accumulates subject to (16),
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 $\beta(1-\delta+B_X)$. The key in the reallocation of labor is industry output and task prices which are given by the following equations:

$$p_{it} = \left(\sum_{j}^{J} \phi_{ij} \left(\tau_{jt}\right)^{1-\theta} \right)^{\frac{1}{1-\theta}}, \tag{23}$$

$$\tau_{jt} = \frac{1}{A_{jt}} \left(\frac{w_t}{\alpha} \right)^{\alpha} \left(\frac{p_{ijt}^E}{1-\alpha} \right)^{1-\alpha}. \tag{24}$$

3.6 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 proportional to the technology adjustment costs. 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 changes that is experienced throughout the whole economy. First is a positive growth rate for the economy-wide technology. Second represents 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 (5), (14), and (24) 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 (12), and A_{jt} as in equation (11). 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 (14) and (20) 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 (23) reveals that industry price is increasing in the task prices proportional to their production weights ϕ_{ij}. From (24) 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 (23) and (24) 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 B.5 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.

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

[29] In this case, the right hand side of log labor productivity equation becomes $(1-\alpha)\log\left(\frac{1-\alpha}{\alpha}\right) + (1-\alpha)\log w_t + \sum_{j=1}^{J} s_{j|i}\log A_{jt} - \sum_{j=1}^{J}(1-\alpha)\, s_{j|i} logp^E_{ijt}$, 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.

[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.

capital to the other task capital:

$$\frac{K^C_{jt}}{K^N_{jt}} = \left(\frac{p^N_t}{p^C_t}\right)\left(\frac{\kappa_j}{1-\kappa_j}\right),$$

which is straightforward from (12) and (13). 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 et al. (2003)), its strong and significant association with RTI (and not with ITI) in Table 6 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:

$$\frac{p^c_{t+1}K^c_{ijt+1} - p^c_t K^c_{ijt}}{p^E_{t+1}K^E_{ijt+1} - p^E_t K^E_{ijt}} = \kappa_j.$$

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

$$\frac{\sum_{j=1}^J p^c_{t+1}K^c_{ijt+1} - \sum_{j=1}^J p^c_t K^c_{ijt}}{\sum_{j=1}^J p^E_{t+1}K^E_{ijt+1} - \sum_{j=1}^J p^E_t K^E_{ijt}} = \sum_{j=1}^J s_{j|i}\kappa_j.$$

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 7, 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:

$$\frac{K^C_{et}}{L_{et}} = \frac{w_{et}}{p^C_t}\frac{1-\alpha}{\alpha}\sum_{i=1}^I\sum_{j=1}^J \frac{L_{eijt}}{L_{et}}\kappa_j,$$

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 8. Furthermore, it provides an explanation for why skill intensity of commuting zones successfully predicts computer adoption too.

4 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.

4.1 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.[31] For occupations I use a modified version of 2 digit SOC codes in order to increase comparability with Goos et al. (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.[32] Occupations and sectors are listed in Table 9 and 10.

[31] The analysis excludes agriculture and government sector.

[32] Agriculture occupations are also dropped from the sample.

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 customer oriented interpersonal interactions.[33] 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 et al. (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.

[33]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.

4.2 Summary: Trends in Employment, and Tasks

The summary of employment changes and mean task scores for occupations and sectors are reported in Tables 9 and 10. Table 9 summarizes occupations in three broad categories, following the job polarization literature. In order to emphasize job polarization, occupations in Table 9 are ranked according to mean hourly wages. Panel A of Table 9 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 10 summarizes level and changes in employment growth of 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 9 and 10 also provide information about mean ITI and RTI scores for occupation and sectors. Panel B of Table 9 suggests two observations regarding average task intensities for occupations. First, general tendency of the two task measures contrasts 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.[34] For sectoral averages a different picture emerges (Panel B of Table 10). 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. 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

[34] The overall correlation coefficient between ITI and RTI is -0.08.

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

4.3 Estimation and Results

4.4 Evolution of Technology

I assume that occupation-specific technology A_{jt} follows an exogenous trajectory that consists of a time-varying economy wide technology term and an occupation-specific component that grows differentially according to interpersonal-service task intensity:

$$\log A_{jt} = (c + \gamma_{ITI} ITI_j) \times trend, \tag{25}$$

where c is some constant, γ_{ITI} determines how technology growth is affected by interpersonal-service ask intensity, ITI_j is the time invariant task score for occupation j, and $trend$ is the linear time trend. This form captures the higher technology adjustment costs associated with interpersonal-service content in equation (11). Therefore the theory suggests that $\gamma_{ITI} < 0$.[35]

[35] Specifically, I assume $\rho_j = \frac{1}{1-(c+\gamma_{ITI} ITI_j)^{-1}}$, and $logA_t = trend$.

Assuming that the share of computing capital, κ_j, is proportional to routine task intensity and the relative price of computing capital falls exponentially the logarithm of the effective price of capital faced by occupation j given by equation (12) is in the following form:

$$\log p_{jt}^{E} = \gamma_{Ei} + \gamma_{Et} - \gamma_{RTI} RTI_j \times trend, \tag{26}$$

where γ_{Ei} captures occupation-specific level parameters, γ_{Et} represents the economy-wide change in the price of non-computing capital, γ_{RTI} determines how much the specific occupation is differentially affected by the common decline in relative prices, RTI_j is the time invariant task score for occupation j, and $trend$ is the linear time trend.[36] The model predicts that more routine-intensive occupations have higher computing capital shares and thus witness greater declines in the task-capital price. Accordingly, $\gamma_{RTI} > 0$ is expected.

4.4.1 Estimation of Employment

I use the model's implied equations in order to estimate the impact of task measures on labor demand. In particular, I estimate the employment equation conditional on industry output and marginal costs. The following shows the log of occupation employment from the model:

$$\begin{aligned} \log L_{ijt} &= \hat{\Phi}_{ij} + (1-\alpha)(1-\theta)\log p_t^{N} + (\alpha(1-\theta)-1)\log w_t + \theta \log p_{it} + \log Y_{it} \\ &\quad - (1-\theta)\log A_{jt} + (1-\alpha)(1-\theta)\log p_{jt}^{E}. \end{aligned} \tag{27}$$

Imposing the assumptions on the evolution of exogenous technology and capital prices and sector-occupation and year-specific effects I get the following estimable labor demand equation:

$$\begin{aligned} \log L_{ijt} &= \zeta_{ij} + \zeta_t + \theta \log p_{it} + \log Y_{it} \\ &\quad - (1-\theta)\gamma_{ITI} ITI_j \times trend - (1-\theta)\gamma_{RTI} RTI_j \times trend + \nu_{ijt}, \end{aligned} \tag{28}$$

where ζ_{ij} and ζ_t represent dummies for sector-occupation and time, respectively, and ν_{ijt} is the iid error term. These capture the impact of industry and occupation-specific technology levels, price of

[36] In particular, I assume $\kappa_j = \gamma_{RTI} RTI_j$ and $\log \frac{p_t^N}{p_t^C} = trend$.

non-computing capital, and average wages.[37]

Table 11 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.

4.4.2 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

[37]In the model workers in different occupations and industries are assumed to be homogeneous and there is a single wage rate for each time period. This feature of the model is shared by several models of structural change that aims to explain employment reallocation. However, sectoral wages across occupations differ in the data. Including actual wages in the labor demand estimations leads to insignificant and small coefficients on wages and does not change the coefficients of key variables. See Goos et al. (2014) for a similar result on European labor demand.

results reported in Table 11 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:

$$Y_{it} = A_{it}\left[\sum_{j}^{J}(\phi_{ij})^{\frac{1}{\theta}}(T_{ijt})^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}}. \tag{29}$$

Optimal task and input allocation decisions imply that the labor demand equation of the hybrid model is the same except that now it includes a term for industry technology:

$$\begin{aligned}\log L_{ijt} \;=\;& \hat{\Phi}_{ij} + (1-\alpha)(1-\theta)\log p_t^N + (\alpha(1-\theta)-1)\log w_t + \theta\log p_{it} + \log Y_{it} && (30)\\ & -(1-\theta)\log A_{jt} + (1-\alpha)(1-\theta)\log p_{jt}^E - (1-\theta)\log A_{it} && (31)\end{aligned}$$

The last component of the summation in (30) 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 (28) 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 12 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 11 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 12. 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 12 and those in Table 11.

4.4.3 The Role of Tasks in The Evolution of Employment 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 13 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 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 subperiods 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.

4.4.4 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 (20) 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:

$$\log Y_{it} \quad = \quad \tilde{\gamma}_i + \tilde{\gamma}_t - \epsilon \log\left(\frac{p_{it}}{P_t}\right) + \tilde{\nu}_{it}, \tag{32}$$

which is log-transformed and market clearing imposed version of equation (20) with industry output consumption weights and aggregate real income captured by industry- and time-fixed effects $\tilde{\gamma}_i$ and $\tilde{\gamma}_t$, and the error term $\tilde{\nu}_{it}$.

As in the labor demand estimation, I provide the estimation of equation (32) 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. $\epsilon < 1$.

4.5 Growth Accounting of Employment

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 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.

4.5.1 Employment Share Growth

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

$$\begin{aligned} \frac{\partial s_{jt}}{\partial t} &= \frac{\partial L_{jt}}{\partial t}\frac{1}{L_{jt}}s_{jt} - \frac{\partial L_t}{\partial t}\frac{1}{L_t}s_{jt} \\ &= \left(\sum_{i=1}^{I}\frac{\partial \log L_{ijt}}{\partial t}s_{i|jt} - \sum_{i=1}^{I}s_{it}\left(\sum_{j=1}^{J}\frac{\partial \log L_{ijt}}{\partial t}s_{j|it}\right)\right)s_{jt}, \end{aligned} \quad (33)$$

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 equation (28), price equation (23), and output demand equation (32), I express (33) in terms of estimated task impacts, elasticity parameters and task scores:[38]

[38] I use the following approximation for the industry marginal cost equation:

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

$$
\begin{aligned}
\frac{\partial s_{jt}}{\partial t} &= \left(\gamma_I ITI_j + \gamma_R RTI_j + \frac{(\theta-\epsilon)}{(1-\theta)}\left(\sum_{i=1}^{I} s_{i|jt}\left(\gamma_I ITI_{it}^{I} + \gamma_R RTI_{it}^{I}\right)\right)\right) s_{jt} \\
&- \left(\frac{1-\epsilon}{1-\theta}\left(\gamma_I ITI_t^A + \gamma_R RTI_t^A\right)\right) s_{jt}, \qquad (34)
\end{aligned}
$$

where $\gamma_I = -(1-\theta)\gamma_{ITI}$, $\gamma_R = -(1-\theta)\gamma_{RTI}$ are estimated task impacts from labor demand equations; ITI_{it}^I and RTI_{it}^I are industry averages of task measures; ITI_t^A and RTI_t^A are economy averages of task measures.[39]

Equation (34) 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.[40]

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.

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

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

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

$$\frac{\partial s_{it}}{\partial t} = \frac{\partial L_{it}}{\partial t}\frac{1}{L_{it}}s_{it} - \frac{\partial L_t}{\partial t}\frac{1}{L_t}s_{it} = \left(\sum_{j=1}^{I}\frac{\partial \log L_{ijt}}{\partial t}s_{j|it} - \sum_{i=1}^{I}s_{it}\left(\sum_{j=1}^{J}\frac{\partial \log L_{ijt}}{\partial t}s_{j|it}\right)\right)s_{it}. \tag{35}$$

Using labor demand, output demand, and price equations (35) can be expressed as the following:

$$\frac{\partial s_{it}}{\partial t} = \frac{(1-\epsilon)}{(1-\theta)}\left(\gamma_I\left(ITI^I_{it} - ITI^A_t\right) + \gamma_R\left(RTI^I_{it} - RTI^A_t\right)\right)s_{it}. \tag{36}$$

The change of employment share depends on the elasticity of substitution in consumption, ϵ.[41] 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.

4.5.2 Actual vs 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 4. 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:

$$WMAPE^{occ} = 100 \times \sum_{j=1}^{J}\bar{s}_j\frac{\left|s^p_{j,2014} - s_{j,2014}\right|}{s_{j,2014}}, \tag{37}$$

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 from the actual on average. WMAPE calculated for occupation predictions is 13.45.[42] In other words, the task-based model on average is off by slightly below 14 percent.

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

[42] The same statistic can be computed for Table 4 of Goos et al. (2014). Their task-based technical change model has WMAPE of 13.38 for European countries between for 1993-2010 period.

Lighter and darker gray bars in Figure 4 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. 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 5 presents actual and predicted employment share changes for sectors. The predictions are based on equation (36). 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:

$$WMAPE^{ind} = 100 \times \sum_{i=1}^{I} \bar{s}_i \frac{\left| s^p_{i,2014} - s_{i,2014} \right|}{s_{i,2014}}, \tag{38}$$

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 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.

4.5.3 Implications for Job Polarization and Structural Change

The disaggregated analysis above strongly suggests ITI as an important driver of occupational and industrial employment growth 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 15 aggregates the actual and predicted employment share changes to occupations grouped according to their place in the wage distribution following Table 9. 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 15 aggregates the employment change predictions for service producing sector following the classification in Table 10 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.

4.5.4 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 et al. (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 B.6 compares the predictions obtained when alternative variables are used in the estimation of the model.[43] 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 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.[44]

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

[43] 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.

[44] 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.

bulk of the predictive capacity of the model comes from interpersonal-service tasks. Comparing individual predictions to total, Table B.6 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 et al., 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 et al., 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.

Whether ITI is part of the routinization framework is extensively studied Sevinc (2017), which 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 et al., 2014; Lee and Shin, 2017). In Figure B.3 and B.4 I show the predictions and actual changes when I model technology growth as a linear function of offshorability.[45] 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.[46] Preferences are conceptually argued to impact both sector (e.g., Kongsamut et al., 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. Therefore, the estimated impact of ITI can be affected by preferences, which is an alternative to the technology perspective of this paper. Although the current specification does not allow a direct control for this possibility, Figure B.5 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, which allow household consumption directly, 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.

[45] The observationally equal case is having capital in the model and assuming faster declines in capital prices in more offshorable tasks (Goos et al., 2014).

[46] 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 et al., 2014), which is outside the scope of the current analysis.

5 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. Interpersonal-service tasks appear 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.

I introduce a generalized structural change model with many occupations and industries that is capable of predicting both the slower productivity growth and rising employment trends associated with interpersonal-service intensive activities observed in the data. Moreover, the model allows, both conceptually and empirically, distinguishing routinization, which has been a key aspect of technological developments in recent decades through increasing use of computers, from the relatively stagnant nature of interpersonal-service tasks which is possibly related to high costs of adopting new technologies in the workplace. This distinction is empirically interesting as the emerging literature on occupational reallocation of labor suggests both routine-biased technical change and structural transformation as being responsible from the employment trends in the labor market.

The model estimates of employment growth suggest 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.

Results of this paper implies that, as long as direct customer influence on the task being performed will somehow be avoided by firms, interpersonal-service tasks are going to continue growing even computers and artificial intelligence replace work previously known as ”non-routine”. Hence, the increasingly interpersonal-oriented workplace across the whole wage/skill spectrum of tasks is likely to remain a key phenomenon even when the growth of the broad service sector reaches to its limit.

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Tables

Table 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 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 B.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 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 B.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 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 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 6: 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 7: Tasks and Technology: Industry ICT Intensification

(Dependent Variable: 100 × 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 8: 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 9: 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 10: 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 11: 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 12: 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 13: 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 14: 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 15: TRENDS IN EMPLOYMENT: ACTUAL VS MODEL

(100 × 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 9 and Table 10. Actual refers to the long change in employment share observed in the data. Column Total reports predictions as described in Figure 4 notes (for Panel A) and 5 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.

Figures

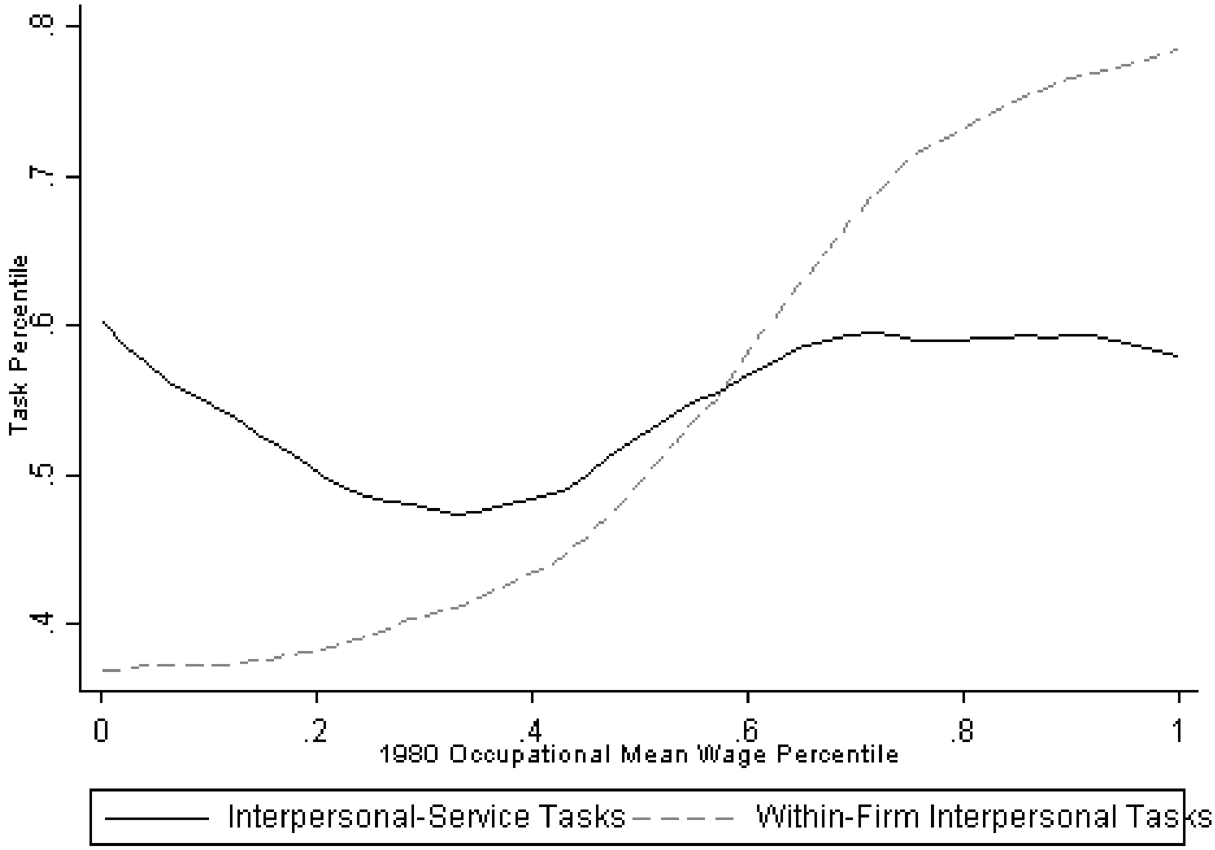

Figure 1: Smoothed Interpersonal Task Scores by 1980 Mean Wage Percentile

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.

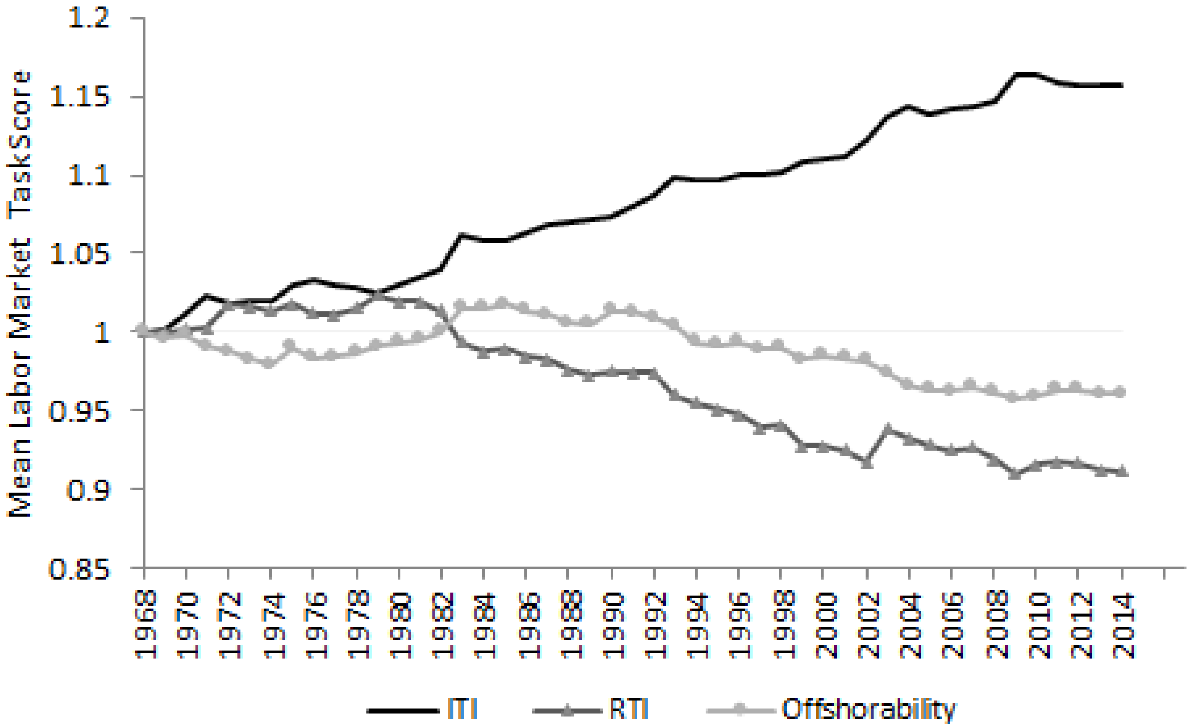

Figure 2: Tasks in the Labor Market, 1968-2014

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.

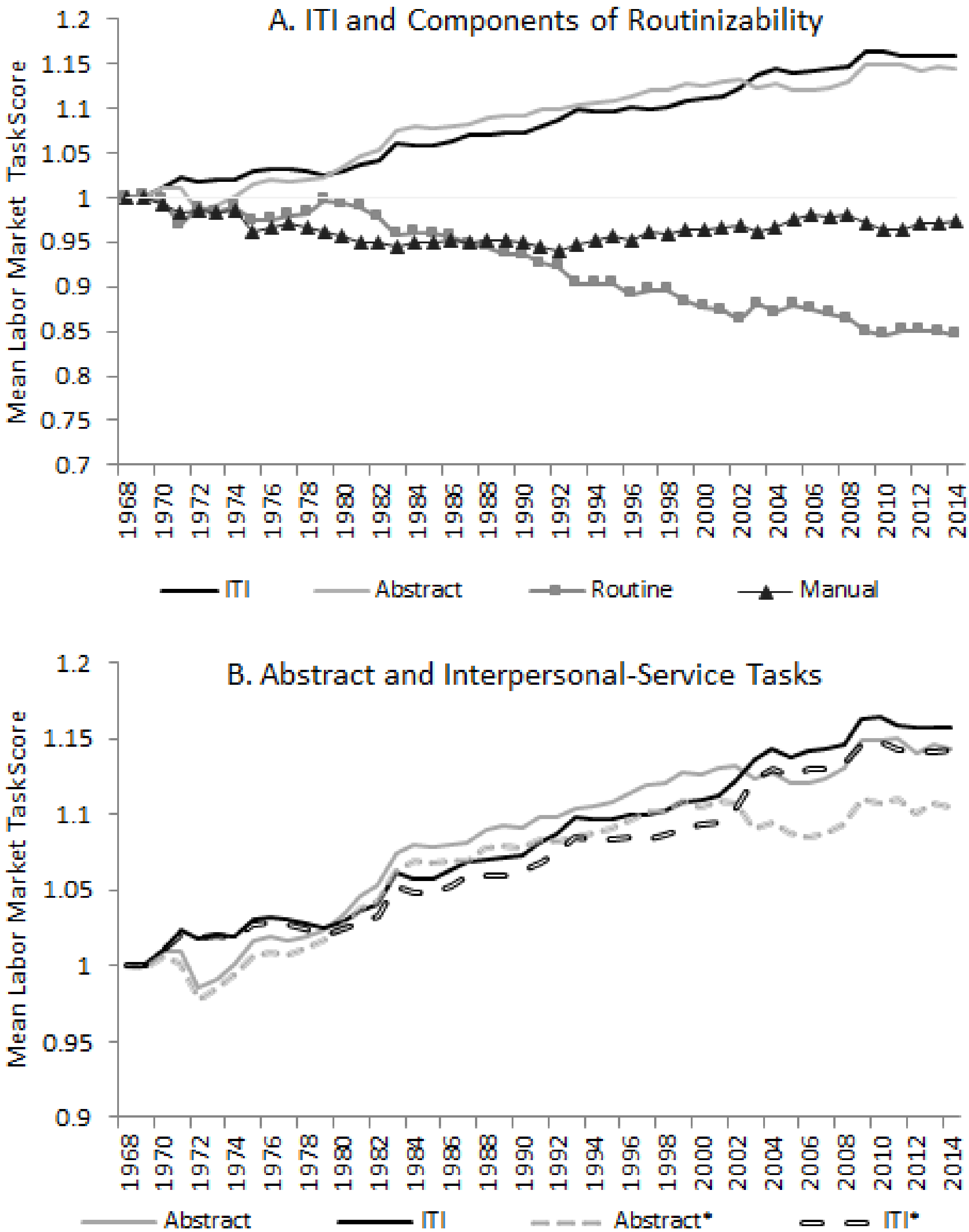

Figure 3: The Evolution of ITI and Routinizability in the Labor Market, 1968-2014

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 et al. (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).

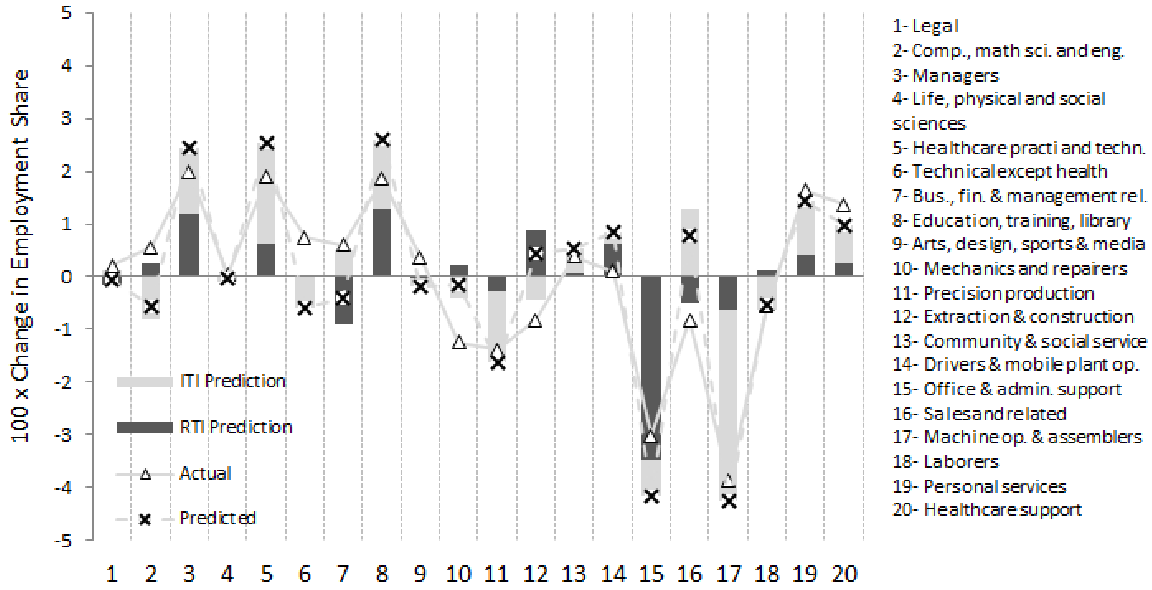

Figure 4: Occupation Employment Share Changes: Actual vs. Predictions

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 34. Parameter values are from column (3) of Table 11 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 11 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 14 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.

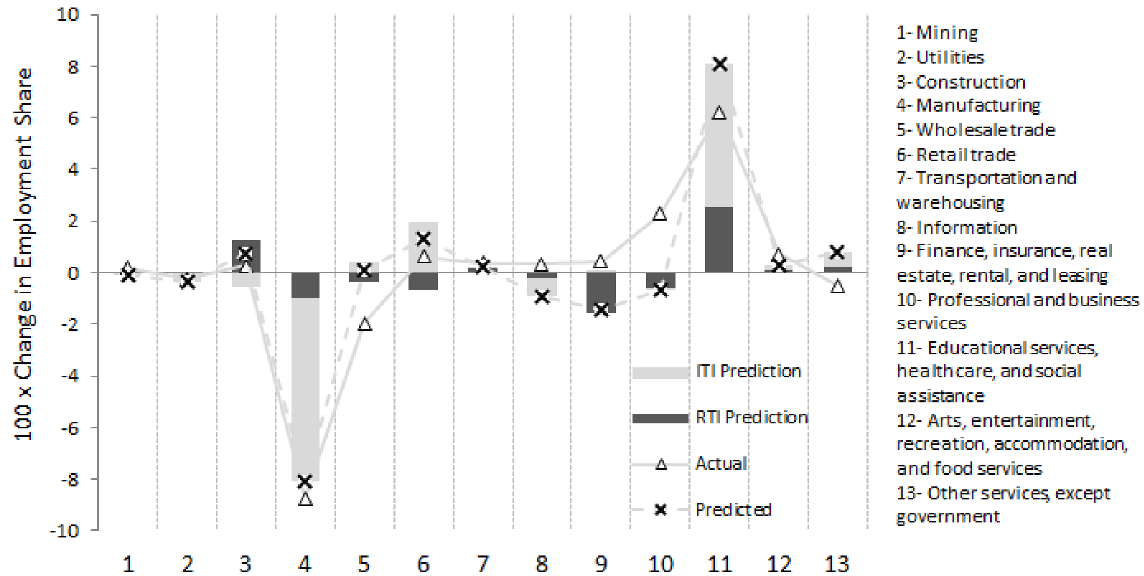

Figure 5: Sector Employment Share Changes: Actual vs. Predictions

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 36. Parameter values are from column (3) of Table 11 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 11 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 14 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.

A.1 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.

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.

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.[47] 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.[48] 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

[47] Labor productivity data are available from `https://download.bls.gov/pub/time.series/ip/`

[48] Capital Flow Table data are available from `https://www.bea.gov/industry/capflow_data.htm`.

follow Autor and Dorn (2013).

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.[49] 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.

[49] The data set is available from `http://doi.org/10.3886/ICPSR08942.v2`.