

Supplementary Material for Interpersonal-Service Tasks and the Change in the US Employment Structure (Not for Publication)

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B.1 Interpersonal-Service Tasks and Other Relevant Task Aspects

Another way to highlight the distinctive feature of interpersonal-service tasks is to compare associations with different aspects of interpersonal skills.

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

Using the interpersonal variables of DOT can provide additional insights on ITI. I show how selected DOT measures are related to ITI and within-firm interactions in Table 3 by partial correlations. The first observation is that the two measures are distinct in their association with DOT tasks reflecting intelligence, data and creative requirements. ITI seems unrelated to these set of characteristics, while within-firm interpersonal tasks are strongly correlated. The fourth row shows the partial correlation between direction, control, and planning variable of DOT, which is the original non-routine cognitive and interpersonal measure of Autor et al. (2003). Insignificant and low correlation with ITI and significant and high correlation with the within-firm measure summarize the difference between two kind of interactions. The two types of interpersonal tasks also have similarities, which are mainly regarding common interpersonal communication that are measured by DOT variables of dealing with people, talking, and people complexity. The last row shows that the variable measuring the task intensity for influencing people is positively related to ITI and does not exhibit significant correlation with within-firm interactions. The main message of the table, which complements Table 2, is that ITI is unattached to task requirements that involve more cognitive and complex abstract skills in contrast to within-firm interpersonal tasks. On the other hand, both are significantly related to people tasks that are dominantly characterized by non-cognitive content, though ITI shows a stronger association.

The literature on task demand discusses the impacts of technology and trade at the task level,

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

Second, I compare ITI with the offshoring measures in the literature. Offshoring hypothesis predicts that tasks, which do not require the material presence of the worker while performing the task, are subject to replacement by international trade in tasks (Blinder, 2009). Following this line of reasoning the literature developed measures of offshorability building on O*NET database (Jensen and Kletzer, 2010; Firpo et al., 2011; Autor and Dorn, 2013). The task characteristic subject to offshorability is conceptually not related to ITI. However the indicators of offshoring in the literature suggest a correlation with ITI score because some of the jobs requiring interactions with customers also necessitates the presence of worker. Nevertheless this overlap is only partial since there are occupations with high ITI and offshorable at the same time such as some clerical and sales occupations; and also occupations that cannot be offshored and low in ITI such as manual intensive repair jobs.¹

The current literature often only discusses the conceptual differences between routinization and offshorability measures, as I did in the previous paragraphs for ITI. Conceptual differences are necessary to establish the essential independence of tasks, however the overlapping elements have the potential to dominate the distinctive characteristics in the constructed measures. Whether this is the case is hard to assess. The main difficulty arises since the constructed measures combine several occupational characteristics that share common elements across different measures. For instance,

¹Blinder (2009) compares a subjective measure of offshoring to an objective measure developed from the O*NET database. The 3 out of 5 O*NET attributes used in the objective measure are also included in ITI, making both measures potentially highly correlated. Blinder (2009) reports that their subjective measure has a low rank correlation ($\rho = 0.16$) with the objective one and that there are large discrepancies between the two. Blinder (2009) and Blinder and Krueger (2013) argue that subjective measures by experts are better in determining the offshorability of occupational tasks. Therefore it can be expected that better offshorability measures exhibit low correlation with ITI, supporting the importance of conceptual differences.

non-routine manual tasks decrease both offshorability and routinizability while routine cognitive tasks increase both. Furthermore, non-routine manual and routine cognitive tasks form quite distinct task aspects. Fortunately, this does not apply when it comes to comparing ITI to main drivers of task demand in the literature since the task variables that make ITI are conceptually quite close, i.e., they are all about customer related interactions. Therefore in the following I compare a task variable that sufficiently characterizes interpersonal-service tasks to several others which span the range of task routinizability and offshorability. Such comparison can be seen as a validity check for the claims suggested as conceptual differences.

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

Finally, Table B.2 provides an overall summary regarding the comparison of task measures by showing average task scores transformed into percentiles for each major occupation category.² Interpersonal-service task measure differs from the routinizability and offshoring mainly because it is jointly and similarly intensive in managerial/professional, clerical and sales, and personal service jobs. This signifies the key properties of ITI discussed above, that is, reflecting the service-task content with a weak association with worker skills.³ In fact, routinizability and offshorability measures are distributed more similarly compared to ITI across major occupation groups. It is also evident from

²Routinizability measure, referred to as RTI, is developed by Autor and Dorn (2013), which is the standardized score of the log of routine task divided by the multiplication of abstract and manual tasks intensity scores. Routine, abstract and manual task scores are developed as a combination of the original DOT variables following Autor et al. (2003). Offshoring measure is developed by Autor and Dorn (2013) following the categorization of Firpo et al. (2011).

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

the table that the mean intensities of within-firm interactiveness and abstract tasks follow very similar distributional patterns.

B.2 The Growing Demand for Interpersonal-Service Tasks and Components of Routinization Hypothesis

Panel A of Figure 3 includes the computed series for abstract, routine, and manual tasks, which form the key task categories of routinizability. The figure captures the rise in non-routine abstract tasks, the decline of routine tasks and relatively stable movement of manual tasks as in Autor et al. (2003). Decline of routine occupations start with 1980s, roughly matching the period when computerization intensifies. The figure also reveals the source of stagnating RTI starting with 2000s. Routine and abstract tasks both slow down compared to 1980-2000 period although the flat movement is more emphasized in abstract tasks.⁴

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

The adjustment yields lower growth in both tasks but in different ways. ITI and its adjusted version decouple starting with early 1980s. The gap widens throughout 1990s then remains roughly the same. This can be potentially explained considering the impact of ITI's positive correlation with the non-routine interpersonal tasks since routinization intensifies after the 1980s and reaches its peak during the 1990s. On the other hand, adjusted abstract task measure disengages from its original since the initial sample period while the difference only gets larger with time. The slowdown in abstract tasks is more emphasized in its adjusted version. More precisely, between 2000 and

⁴In an attempt to update Autor et al. (2003), Autor and Price (2013) documented the flat movement in abstract tasks for the first time.

2014 the abstract measure that is orthogonal to ITI grows at a rate of -0.01 percent per annum compared to average annual growth rate of 0.41 percent between 1980 and 2000. In contrast, adjusted ITI indicates a more pronounced rise by growing annually 0.30 percent after 2000, which is almost identical to the growth of the original ITI measure during the same period and quite close to the historical growth rate before 2000.

B.3 Interpersonal-Service Tasks and Productivity Growth

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

The recent literature on tasks and technology is dominated by routinization hypothesis. Similar to the role of sector-specific productivity growth in the structural change models, in the literature the success of RTI in explaining employment reallocation (out of high RTI tasks) stems from the fact that RTI-intensive occupations have a faster productivity growth as a result of more intensive computerization [Goos et al. \(2014\)](#).

Since both ITI and RTI are important task aspects in terms of the reallocation of employment, the comparison between the two with respect to technology is the main discussion in this section. Recently, both technological growth that is slower in service activities ([Barány and Siegel, 2017](#); [Duernecker and Herrendorf, 2017](#)) and faster in routinizable ones ([Goos et al., 2014](#); [Autor and Dorn, 2013](#)) are studied, but characterization on how the two connect to the technological change at the task level remains obscure. Below I first show that the stylized view on productivity and tasks hold at industry level.⁵ Then I provide novel evidence on how interpersonal-service content relates to developments in ICT technologies, which are well known to be the basis of recent routinization experience.

If customers really act as a brake on productivity, we should observe slower labor productivity

⁵Unfortunately, to the best of my knowledge there exist no data that measure productivity across years at the occupation level.

growth not only in the broad service sector but also in detailed sectors that more intensively employ interpersonal-service tasks. While the well known examples of industries with slowest labor productivity growth or with highest relative price increases such as health and education services can be easily recognized as high-ITI industries, it is of interest of this section whether this association holds throughout the economy. In addition, if routinization enables more exposure to labor-saving technologies, labor productivity should grow faster in industries with higher RTI. I formally test these claims using labor productivity data from BLS between years 1987-2014 below. The productivity data is detailed at finer industry categories however they cannot be reliably matched to industry codes in CPS or Census where I compute employment-weighted industry-task intensities. Instead, I generate industry task intensities for 12 broad NAICS categories. In particular, I estimate the following equation:

$$a_{it} = \sum_{x \in X} \beta_{xm} (x_m \times time) + d_t + \eta_i + u_{it} \quad (1)$$

where a_{it} is the log of labor productivity index for detailed industry i at time t ; x_m is the time invariant measure of broader sector task intensity⁶ of task x performed by the workers in broader sector m in a set of tasks denoted by X ; $time$ is a running variable for year; d_t are year dummies; η_i are industry dummies. β_{xm} captures the impact of industry task intensity on the growth rate of productivity in broader NAICS sector m .

Table B.5 column (1) reports β_{ITI} and its standard error. As expected, the coefficient of ITI is significantly negative and statistically significant. Sectors with higher ITI exhibits slower labor productivity growth. Column (2) reports positive and significant coefficient for β_{RTI} . The last column includes both RTI and ITI in the regressions, where reported coefficients shrink only little compared to individual estimates under other columns. Industry labor productivity trends are in line with the predictions of the stylized view.

⁶I simply use standardized long-run mean task scores for each sector using CPS labor supply weights. Task score rankings across sectors are remarkably stable over time, the evidence for which is available upon request.

Appendix Tables

Table B.1: TOP AND BOTTOM INTERPERSONAL OCCUPATIONS

A. Interpersonal-Service Intensity (ITI) Rankings	
1. Top 15 Occupations	2. Bottom 15 Occupations
Police and detectives	Mathematical Technicians
Correctional Officers	Woodworking Machine Setters, Operators, and Tenders, Except Sawing
Licensed Practical and Licensed Vocational Nurses	Shoe Machine Operators and Tenders
Child, Family, and School Social Workers	Sawing Machine Setters, Operators, and Tenders, Wood
Registered Nurses	Foundry Mold and Coremakers
Parking Lot Attendants	Pressers, Textile, Garment, and Related Materials
Health Educators	Computer Programmers
Clergy	Remote Sensing Scientists and Technologists
Bartenders	Proofreaders and Copy Markers
Animal Control Workers	Prepress Technicians and Workers
Forest Fire Fighting and Prevention Supervisors	Actuaries
Substance Abuse and Behavioral Disorder Counselors	Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic
Travel Agents	Packaging and Filling Machine Operators and Tenders
Pharmacists	Tool and Die Makers
Physical Therapists	Forging Machine Setters, Operators, and Tenders, Metal and Plastic
B. Within-Firm Interactions Intensity Rankings	
1. Top 15 Occupations	2. Bottom 15 Occupations
Chief Executives	Barbers
Clergy	Sewers, Hand
Medical and Health Services Managers	Postal Service Mail Carriers
Education Administrators, Preschool and Childcare Center/Program	Pressers, Textile, Garment, and Related Materials
Urban and Regional Planners	Demonstrators and Product Promoters
First-Line Supervisors of Mechanics, Installers, and Repairers	Shoe and Leather Workers and Repairers
Actors	Camera and Photographic Equipment Repairers
First-Line Supervisors of Office and Administrative Support Workers	Automotive and Watercraft Service Attendants
First-Line Supervisors of Construction Trades and Extraction Workers	Forging Machine Setters, Operators, and Tenders, Metal and Plastic
Spa Managers	Textile Knitting and Weaving Machine Setters, Operators, and Tenders
Licensed Practical and Licensed Vocational Nurses	Sewing Machine Operators
Aircraft Cargo Handling Supervisors	Postal Service Clerks
Dentists, General	Shoe Machine Operators and Tenders
Financial Managers, Branch or Department	Door-To-Door Sales Workers, News and Street Vendors, and Related Workers
Advertising and Promotions Managers	Furniture Finishers

Table B.2: AVERAGE TASK SCORE PERCENTILE RANK IN OCCUPATION GROUPS

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

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

Table B.3: ROUTINIZATION, OFFSHORING, AND SERVICE SECTOR SPECIALIZATION

(Dependent Variable: Service Sector Intensity)

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

Notes: The table shows OLS estimates of dependent variable on different interpersonal measures shown in each row. Dependent variable is 1980-2010 long-run mean employment of service sector workers relative to all employment in an occupation. There are 322 observations in each specification. All regressions are weighted by occupations' 1980 employment shares. Columns (2) and (4) include major occupation group dummies. Occupation groups are listed in Table 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 B.4: CHANGING TASK DEMAND AND WITHIN-FIRM INTERACTIONS

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

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

Table B.5: LABOR PRODUCTIVITY GROWTH AND TASKS

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

	(1)	(2)	(3)
<i>Time Trend</i> × ITI	-0.22*** (0.06)		-0.16*** (0.05)
<i>Time Trend</i> × RTI		0.61*** (0.12)	0.53*** (0.14)
R^2	0.61	0.62	0.62

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

Table B.6: PREDICTIONS WITH ALTERNATIVE MEASURES: ACTUAL VS MODEL

(100 × Employment Share Change, 1987-2014)

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

Notes: The predictions use task coefficients of alternative measures of ITI (ITI* in the table) and RTI (RTI* in the table) as defined in the text. For all other details see Figure 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.

Appendix Figures

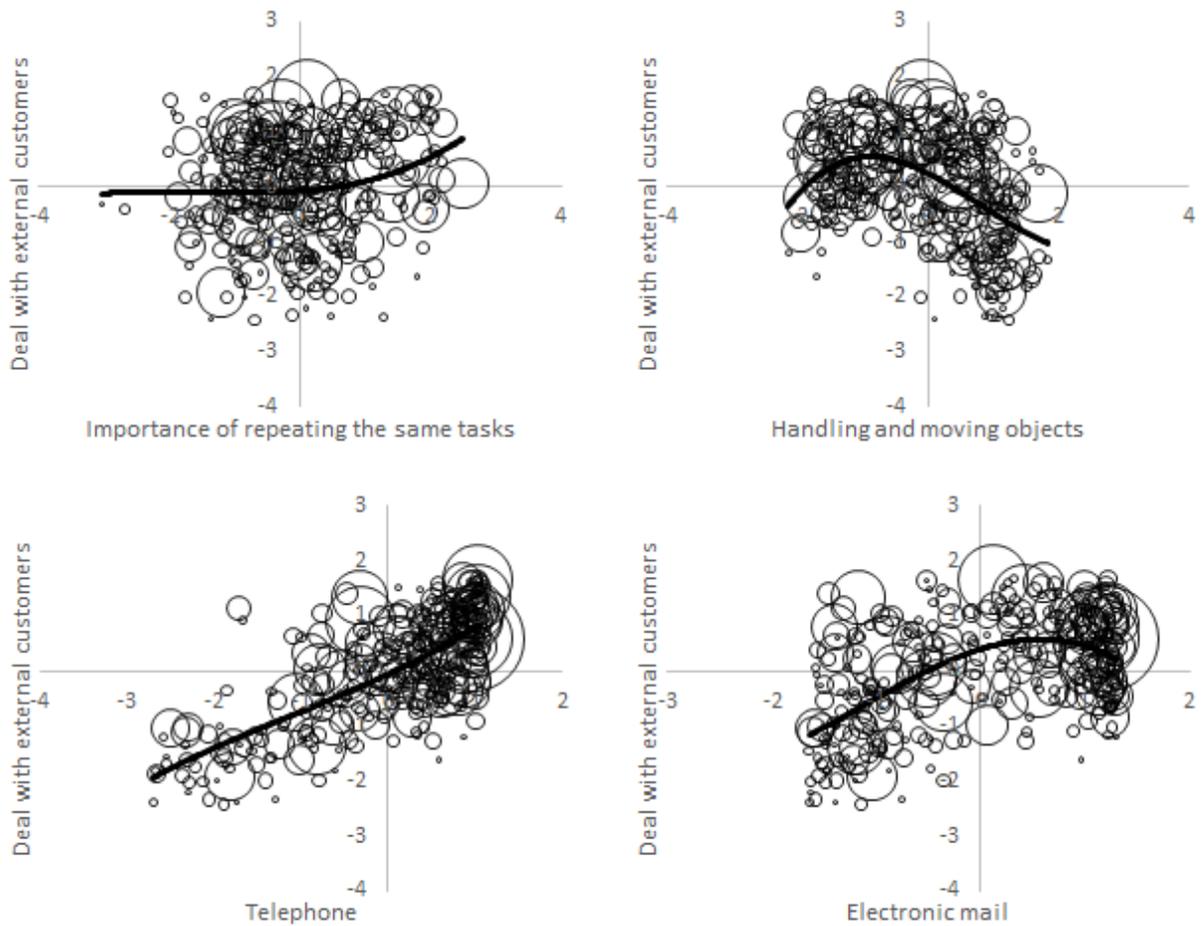


Figure B.1: ITI vs. Elements of Routinization and Offshoring

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

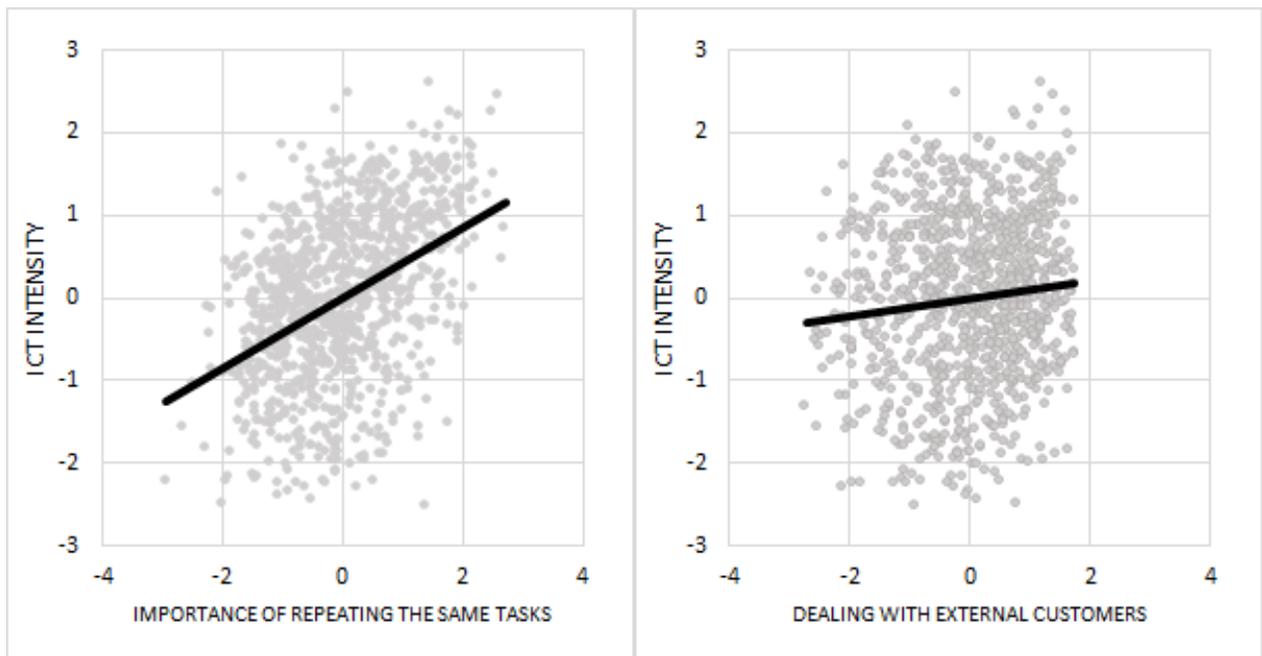


Figure B.2: ICT Intensity and Tasks: Alternative Variables and Detailed Occupations

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

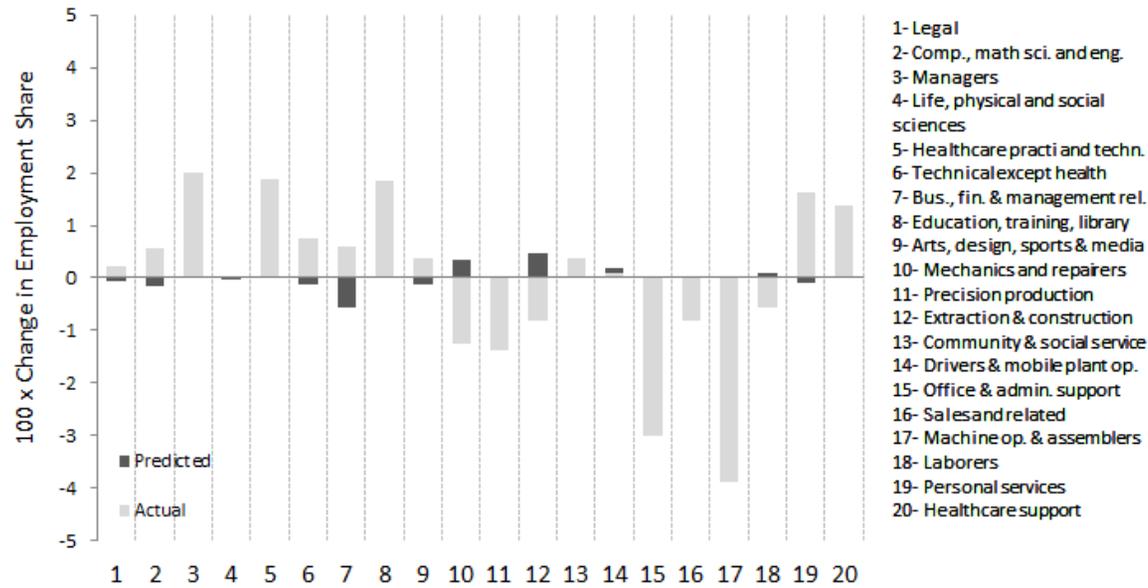


Figure B.3: Performance of Offshorability Measure: Actual vs. Predicted Changes in Occupation Employment Shares

Notes: The figure shows the actual and predicted occupation employment share changes from the estimation of the task model of offshorability which provides the coefficient of the offshorability measure. For other details of the computation see Figure 4 notes.

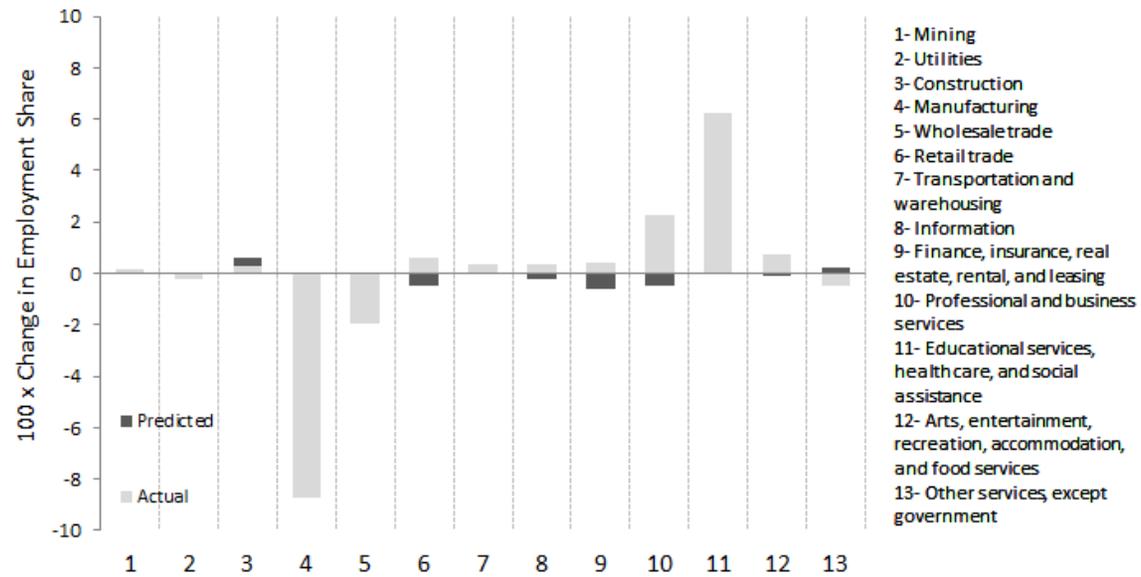


Figure B.4: Performance of Offshorability Measure: Actual vs. Predicted Changes in Sector Employment Shares

Notes: The figure shows the actual and predicted occupation employment share changes from the estimation of the task model of offshorability which provides the coefficient of the offshorability measure. For other details of the computation see Figure 5 notes.

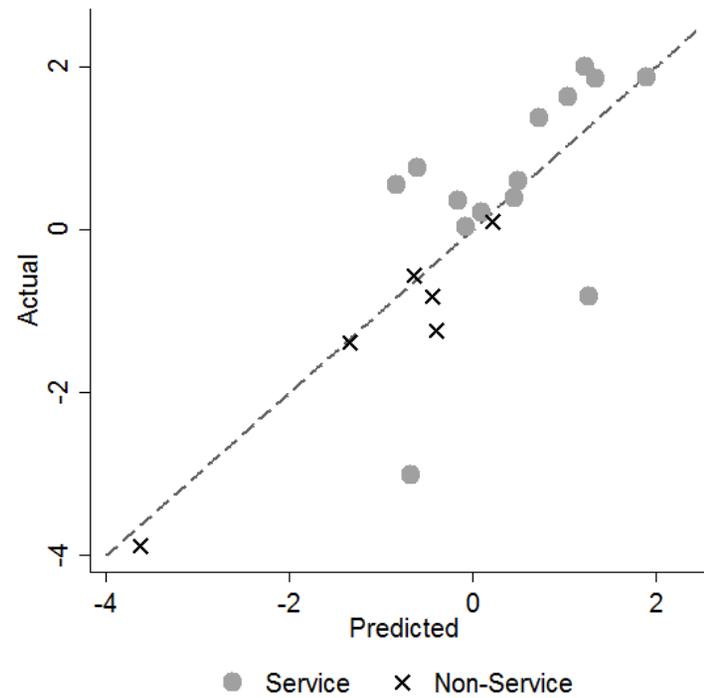


Figure B.5: ITI and Employment Growth: Actual vs. Predicted Changes Employment Shares by Service Intensity of Occupations

Notes: The figure plots the actual vs. predicted occupation employment share changes from the estimation of the task model. The predictions are ITI's individual contributions as in Figure 4. The service occupation definition is adopted from [Duernecker and Herrendorf \(2017\)](#). Non-service occupations are mechanics and repairers; extraction and construction workers; precision production workers; machine operators and assemblers; drivers and mobile plant operators; laborers in transport, manufacturing, construction and extraction. All other occupations belong to service intensive occupations.

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