Routinization, Within-Occupation Task Changes and Long-Run Employment Dynamics

Davide Consoli
Giovanni Marin
Francesco Rentocchini
Francesco Vona

SCIENCES PO OFCE WORKING PAPER n° 08/2019

CONTACT US

OFCE
10 place de Catalogne | 75014 Paris | France
Tél. +33 1 44 18 54 87

www.ofce.fr

WORKING PAPER CITATION

This Working Paper:

Davide Consoli, Giovanni Marin, Francesco Rentocchini, Francesco Vona
Routinization, Within-Occupation Task Changes and Long-Run Employment Dynamics
Sciences Po OFCE Working Paper, n° 08

Downloaded from URL : www.ofce.sciences-po.fr/pdf/dtravail/OFCEWP2019-08.pdf
DOI - ISSN

ABOUT THE AUTHOR

Davide Consoli INGENIO (CSIC-UPV)
Email Address: davide.consoli@ingenio.upv.es

Giovanni Marin Department of Economics, Society and Politics, University of Urbino Carlo Bo, Italy
Email Address: giovanni.marin@uniurb.it

Francesco Rentocchini Department of Economics, Management and Quantitative Methods, University of Milan, Italy and Southampton Business School, University of Southampton, UK
Email Address: francesco.rentocchini@unimi.it

Francesco Vona OFCE Sciences-Po and SKEMA Business School, Université Côte d'Azur
Email Address: francesco.vona@sciencespo.fr

ABSTRACT

This study contributes to the literature on routinization and employment by capturing within-occupation task changes over the period 1980-2010. The main contribution is the measurement of such changes combining two data sources on occupational task content for the United States: the Dictionary of Occupational Titles and the Occupational Information Network. We show that within-occupation task change: i) accounts for 1/3 of the decline in routine-task use; ii) accelerates in the 1990s, decelerates in the 2000s but with significant catching-up; iii) is associated with educational upgrading in several dimensions and iv) allows escaping the employment decline conditional on initial routine-task intensity.

KEY WORDS

Tasks, routinization, technological change, employment dynamics, race between technology and education

JEL

J23, J24, O33

* We wish to thank David Autor, Georg Graetz, Ariell Reshef, Anna Salomons and seminar participants at 3th Task Conference (Nuremberg), at the workshop "Beyond Routinization" (Nice) and at the EURKIND conference (Valencia) for constructive comments. Francesco Vona wishes to acknowledge fruitful discussions with his former Ph.D. advisor, Prof. Mario Amendola, from whom (several years ago now) he gained the much-needed insights for the inception of this project. Financial support acknowledgements: the French government, through the UCA-JEDI Investments in the Future project managed by the National Research Agency [ANR-15-IDEX-01] (FV); CSIC and Ministerio de Economía y Empresa de España [ECO2017-86976-R] (DC).

1 Introduction

The task approach has become the main framework of reference to analyse structural changes in labour markets (Autor, Levy and Murnane, 2003; Acemoglu and Autor, 2011; Goos, Manning and Salomons, 2014) as well as their implications for inequality (Autor, Katz and Kearney, 2008; Lemieux, 2008). Classifying occupations by their task content has proved particularly effective in explaining labour market dynamics, and in identifying the jobs that are more exposed to structural transformations, such as technological change and globalization. However, the empirical literature that stems from this now prominent approach focuses on changes at the ‘extensive’ margin, that is, reallocation of employment between occupations whose task content is held constant at some initial or average level. Critically, a framework that assumes that job tasks are static is likely to be inaccurate when it comes to capturing qualitative transformations of work activities and, thus, of the associated skills, especially over extended time periods. Furthermore, the task approach has the potential to better inform changes in training and educational policies against the backdrop of the so-called race between technology and education (Goldin and Katz, 2007; Acemoglu and Autor, 2011). Not only does a static measure of occupational task content systematically understate the extent to which job reallocation takes place (Autor, 2013), but it also fails to detect the task-skill gaps that should guide these policy changes (Vona and Consoli, 2015).

Although the seminal study by Autor, Levy and Murnane (2003; henceforth ALM) calls attention to variations at the ‘intensive’ margin (i.e., changes in job tasks within an occupation), this particular dimension has remained relatively under-explored due to data limitations. The present study fills this gap by creating a measure of routine-task orientation for 322 occupations based on two main data sources for the United States (US), namely, the Dictionary of Occupational Titles (DOT) and its successor, the Occupational Information Network (O*NET). Such a measure allows us to build a consistent time series of within-occupation task changes over a thirty-year period, from 1980 to 2010. Using this measure, we shed light on unexplored aspects of the long-term structural changes in the US labour market spanning various phases of technology diffusion.

Within-occupation task change is by definition a long-term phenomenon that requires the mutual adaptation of demand and supply of skills. The paucity of suitable data sources offers a cue to the first contribution of the present paper. A thorough analysis of how job content evolves requires a data series that covers a long timespan. The two most frequently used resources are the DOT, which was updated until 1991 when O*NET, the second source, was officially released. Despite being designed for a similar purpose, however, the match between these two resources for the purpose of generating a long time series presents some challenges. A key issue is that the complexity of the data has increased significantly with the inception of O*NET, so that using task items from these two sources, while maintaining consistency, requires a high degree of discretion on the part of researchers (Autor, 2013).

Section 2 details the procedure for the identification of matching items in DOT and O*NET that allows us to construct a time-varying measure of job tasks for 322 occupations. The guiding criterion to operationalise the matching between the two sources is the similarity between the task title and the task description. Based on this matching, we build an index of routine task intensity (RTI[1]) that also accounts for within occupation task changes. We show that the proposed procedure is successful in matching the moments of the distributions of the underlying task measures for the two data sources and the different decades.

Section 3 presents descriptive evidence of changes in the task content of occupations, using standard data sources, i.e., the decennial Census and American Community Survey (ACS), to construct weighted averages of occupational task measures. First, we find that within-occupation task change accounts for 37% of the overall decline in routine task use between 1980-2010. The within-occupation component is especially important in the 1990s (67% of the decadal change), while its incidence declines in the 2000s. Second, beneath the decrease of aggregate RTI there is substantial change in the distribution of work tasks. In particular, we observe a catching-up in routine-task intensity during the last decade. Third, changes in the task content of occupations are heterogeneous across sectors and broad occupational groups. In the 1990s, de-routinization mostly occurred in abstract occupations and was stronger for non-manufacturing sectors. The 2000s marked a reversal of this trend, with the process of de-routinization being concentrated among blue collars and clerical occupations and stronger in manufacturing.

In Section 4, we explore the drivers and the consequences of within-occupation task changes. First and as an additional test of our new measure, we find that change in computer use at work in the 1990s goes in the expected direction: a positive association with within-occupation changes in analytical and interactive tasks, and a negative association with changes in routine tasks and with changes in routine-task intensity. Second, using detailed information on the classification of educational programmes in the US, we explore the extent to which the educational system responded to technology-driven shifts in work content. The main result is that changes in the task content of occupations predict a statistically significant portion of changes, not only in the share of graduates and post-graduates, but also in the number and type of educational programmes. Third, we assess the association between decennial employment growth and within-occupation task

[1] RTI is increasing when the intensity of repetitive cognitive and manual tasks grows relative to the intensity of cognitive analytical and interactive tasks, such as creativity, problem-solving, intuition and social perceptiveness.

changes, controlling for, *inter alia*, initial routine task intensity. We find that changes in RTI are associated with decennial employment growth over the entire timespan, the strongest effect being in 1990s. Our findings also confirm that the association between de-routinization and employment growth is mostly concentrated among clerical jobs. Finally, because task reconfigurations are bounded, the role of within-occupation task shifts may be underestimated for Abstract occupations. We use the matched DOT-O*NET task items to build a measure of task variety for non-routine tasks in the spirit of the Deming's (2018) complementarity between social and cognitive skills. We find that such a measure is positively associated with employment growth for Abstract occupations, which reveals an adjustment mechanism that mostly occurs through the increase in the number of complex tasks.

These results contribute various streams of research using the task approach to assess the relationship between technological change and labour market outcomes (ALM, 2003; Acemoglu and Autor, 2011). To begin with, our new database based on the combination of DOT and O*NET gives us the opportunity to analyse a time period that is both longer or more recent compared to previous studies on within-occupation task changes (ALM, 2003; Spitz-Oener, 2006; Ross, 2017a,b). The most comprehensive study by Spitz-Oener (2006) focuses on Germany, but only until 1999 and without focusing on long-term employment growth. Our study also adds to prior work by Lin (2011) on new occupations and technology diffusion in US cities, with the main difference being that Lin tracks new job titles in the census classification based on the DOT over the period 1980-2000, while we study how the task content of both existing and new occupations evolves between 1980 and 2010.

Furthermore, the present study differs from closely related works which adopt job ad data from online or digital sources (Atalay et al., 2017; Deming and Kahn, 2018). Although very promising in terms of accuracy in the construction of new task measures at both the firm- and the occupation-level, these studies are mainly characterised by a lack of adequate sample representativeness to build the task measures, especially for low-skilled workers, and by a short (Deming and Kahn, 2018) or not up-to-date (Atalay et al., 2017) time dimension.[2] In particular, our work complements Atalay et al. (2017) in that, while their measure better captures task change among abstract occupations, ours better captures task change among clerical and blue collar jobs. Also, their study focusses on explaining wage inequality, while ours focusses on long-term employment dynamics and skill upgrading associated with within-occupation task changes.

[2] For instance, the Burning Glass data used in Deming and Kahn (2018) cover a short period of time (2010-2015), while Atalay et al. (2017) analysis focuses only until 2000.

Finally, our work adds to the recent theoretical literature of task directed technical change. Acemoglu and Restrepo (2017) show that the displacement effect of routine labour-replacing technology is counterbalanced by the emergence of new, more complex, high-skilled work activities. The empirical analysis of the present paper offers a more nuanced view by showing that, while occupations that de-routinize the most exhibit positive employment dynamics, the bulk of within-occupation shifts occurred among middle-skill clerical and manual jobs. In this sense, our findings lend support to the evidence provided by Beaudry et al. (2016) about the reversal in the demand for high-skilled workers that triggered a shift down the occupational ladder towards jobs that were traditionally performed by lower-skilled workers.

The remainder of the paper is organized as follows. Section 2 details the main sources and the procedures for the construction of our DOT-ONET database. This is followed in Section 3 by a series of detailed descriptions of evidence on the evolution of within-occupation task changes over the period 1980-2010. Section 4 follows up on that and presents regression analyses, organized in three steps: the association between computer use at work and task configuration; changes in education supply associated with shifts in occupational task content; and employment outcomes by occupation and by macro-sectors. Section 5 summarizes and concludes.

2 Within-occupation task measures

2.1 Data sources

We combine information from different data sources to develop a consistent picture in the change of skill/task inputs over a thirty-year time period. In particular, we rely on the 1977 and 1991 editions ('Fourth' and 'Revised Fourth', respectively) of the DOT and the 2002 (version 4.0) and 2012 (version 18.0) editions of O*NET. Information on employment and educational attainment is retrieved from Census-based microdata, following recent literature (e.g., Autor and Dorn, 2013). We also use Integrated Public Use Micro Samples (IPUMS, Ruggles et al., 2018): for years 1980, 1990 and 2000 we use the 5% sample of the decennial censuses, while for 2010 we combine three waves (2010, 2011, 2012) of the American Community Survey (ACS), which covers a representative sample of 1% of the US population.

Combining these data sources, we build a balanced panel of 322 occupations based on the harmonized *OCC1990* occupational classification from IPUMS. This raises the issue of how to construct the task measures for the panel of 322 occupations aggregating information from DOT and O*NET, which are available at a much finer level of aggregation.[3] ALM (2003) use weights of the April 1971 CPS Monthly File (National Academy of Sciences, 1981) and retrieve the employment shares of fine-grained job titles in the DOT for one single year (1971). This procedure, however, automatically eliminates the variation in within-task intensity associated with the emergence of new jobs with task configurations adapted to new technologies (Lin, 2011). Since new jobs are important drivers of employment growth (Acemoglu and Restrepo, 2017), we follow Lin (2011) and use uniform weights to aggregate the task content of detailed occupational titles from DOT and O*NET to the level of the 322 occupations of our analysis. In so doing, within-occupation task change also captures the emergence of new job titles and changes in the task content of the occupation.

2.2 Measure

The key variables for our analysis are measures of occupational skill requirements and task intensity. Previous studies have relied on one of the two sources available for the US, namely, the 1977 and 1991 editions of DOT (e.g., ALM, 2003) or O*NET (e.g., Acemoglu and Autor, 2011). One of the main contributions of the present paper is the elaboration of a novel matching procedure to merge DOT and O*NET and the extension of the time horizon of the analysis.

The main critical issue is that O*NET has a comparatively higher number of task-related variables (approximately 400) compared to DOT (44). Moreover, O*NET measures have different scales: the ordinal ‘level’ scale (0-7) and the ordinal ‘importance’ scale (1-5).[4] This is also recognised by Autor (2013, p. 192): “When the DOT was replaced by the O*NET in 1998, *the complexity of the database increased by an order of magnitude*. Version 14.0 of the O*NET database, released in June of 2009, contained 400 separate rating scales, which is almost half as many scales as the number of occupations coded by O*NET […] In practice, this means that *researchers who wish to use these databases as sources for task measures are essentially required to pick and choose among the plethora of scales available*, a problem that is much more severe for O*NET than for DOT.” [emphasis is our own]. Consequently, the task selection originally proposed by ALM (2003) is not suited to our purpose and, due to the constraints highlighted above (high dimensionality and plurality of scales in O*NET), some degree of freedom in the choice of the ideal task measures following researcher discretion is critical.

[3] The occupational classification used in the two versions of DOT features about 12,000 occupations, while the occupational classification used in the two versions of O*NET that we use include, respectively, 900 (O*NET 4.0) and 924 (O*NET 18.0) occupations according to the Standard Occupational Classification (SOC) at the 8-digit level.
[4] These scales are the ones used in O*NET for the sections of our interest: abilities, skills, knowledge and work activities. Other sections such as 'work context' are evaluated according to other specific scales (context, 1-5).

To develop our matching procedure, we follow three general rules. The first two concern the suitability of items that are defined according to the degree of similarity in the *task title* and *task description*. Because O*NET was designed as the natural successor of DOT (Truthan and Karman, 2003), our main reference for the matching exercise is the summary of the DOT variables (occupations and work content) that have been converted to fit the relational model of O*NET as detailed in the first O*NET Data Dictionary (1998). Subsequent versions of this publication do not contain explicit references to DOT. Accordingly, we thoroughly examined variable descriptions in both sources to search for suitable matches. To illustrate, we consider that the DOT variable *Clerical Perception* ("the ability to perceive pertinent detail in verbal or tabular material. Ability to observe differences in copy, to proofread words and numbers, and to avoid perceptual errors in arithmetic computation") bears a very similar title and description to the O*NET item *Clerical* ("knowledge of administrative and clerical procedures and systems such as word processing, managing files and records, stenography and transcription, designing forms, and other office procedures and terminology").

Our third general rule has been to maintain *similar scales* for task scores in the two databases. Notably, we picked task measures which have ordinal (Likert-type) scales. The problem here is that, while all O*NET task scores are defined on an ordinal scale, DOT assigns task scores using either an ordinal scale or dichotomous value. An example is "Direction Control and Planning" (DCP), which can either be present (equal to 1) or absent (equal to 0) in the DOT. Our choice to select items with similar scales avoids loss of information due to the transformation of ordinal variables into dichotomous ones and avoids manipulations that could alter the pattern of task changes through time.

Following these general rules, we identify suitable DOT items that correspond to the four dimensions of occupational task requirements identified by ALM (2003) as those that are particularly affected by automation and Information and Communication Technologies (ICTs): non-routine cognitive tasks (analytical and interactive), routine cognitive tasks and routine manual activity. Our first search yielded 16 different items, four for each of the dimensions of occupational task requirements that can be meaningfully associated between DOT and O*NET.[5] In a second iteration we further reduced the selection to four items (one per dimension) following the aforementioned three criteria. These four items have been subsequently used to build an occupational task intensity measure.

[5] Details on the matching for the 16 different variables are provided in Appendix A1 and are relevant for the analysis we provide on task variety and multitasking (see Section 4 and Table A1).

Table 1 shows the DOT-O*NET matching items and reports the scale of each in the two data sources. When more than one candidate item was found in O*NET, we took the average value. To illustrate, we use the case of MATH and MANUAL. For two measures the scale is similar (MANUAL and CLERIC, with 1-5 level in DOT and 1-5 importance in O*NET), while it is different for MATH and LANGUAGE.[6] The discrepancy is due to the different range between levels in DOT and levels in O*NET (DOT scale of 1-6 vs O*NET 0-7). However, as the distribution of O*NET "level" is bounded, in most cases, between 1-6, we truncate the extreme values to 1 (bottom) and 6 (top).[7] Consequently, we end up with 4 DOT variables linked to their corresponding O*NET match on similar scales.

Table 1 – Match DOT-O*NET

Task category (ALM, 2003)	DOT variable	DOT scale	O*NET variable	O*NET scale
Non-routine analytical	MATH: Mathematical development	1-6	Average of: - Mathematics (knowledge, 2.C.4.a, level) - Mathematics (skill, 2.A.1.e, level)	0-7 ↓ 1-6
Non-routine interactive	LANGUAGE: Language development	1-6	Speaking (skill, 2.A.1.d, level)	0-7 ↓ 1-6
Routine manual	MANUAL: Manual dexterity	1-5	Average of: - Manual dexterity (ability, 1.A.2.a.2, importance) - Arm-hand steadiness (ability, 1.A.2.a.1, importance)	1-5
Routine cognitive	CLERIC: Clerical perception	1-5	Clerical (knowledge, 2.C.1.b, importance)	1-5

Notes: Correspondence between the main DOT task categories used in ALM (2003) with O*NET task categories.

Subsequently, building on existing literature (Autor and Dorn, 2013; Goos et al., 2014) we combine matching DOT-ONET items into a normalised occupation-specific (*o*) and time-varying (*t*) index of routine intensity:

[6] The 'level' scale refers to the proficiency that is required in performing a task, while the 'importance' scale considers how important the task is for the occupation. Even though the two scales appear to be conceptually different, scores for the same task are always very strongly correlated. The correlation between 'level' (0-7) and 'importance' (1-5) for the selected tasks is very strong: 0.93 (0.95 rank correlation) for Clerical (2.C.1.b), 0.94 (0.94 rank correlation) for Manual Dexterity (1.A.2.a.2) and 0.95 (0.95 rank correlation) for Arm-hand Steadiness (1.A.2.a.1), our proxy for non-routine manual tasks.

[7] For the three tasks for which we use the level scale in O*NET, the level is greater than 6 in just two cases: Typists (Clerical, level 6.23 for year 2010) and General office clerks (Clerical, level 6.03 for year 2010). This means that truncation at the top entails very little loss of information. Regarding truncation at the bottom, this happens in 281 cases over a total of 1,932 occupation * task * year cases (14.5 percent).

$$RTI_{o,t} = \log\left(\frac{CLERIC_{o,t}+MANUAL_{o,t}}{MATH_{o,t}+LANG_{o,t}}\right). \quad (1)$$

The index captures the relative routine task requirements and, thus, it measures the exposure to routine-replacing technical change of an occupation. Following the rationale of ALM (2003, p. 1287) we focus only on routine cognitive and routine manual tasks, and non-routine analytic and non-routine interactive tasks. In contrast to recent literature on the variation within the task content of occupations (Atalay et al, 2018; Ross, 2017a), we employ an index of routine intensity. We prefer this to the single measures used in prior studies because the index can smoothen the movement in the task measures due to the changes in scales and classification between DOT and O*NET, and thus it is more suitable for the analysis of long-term changes. Moreover, the index captures the relative importance of routine tasks with respect to non-routine tasks, which is the key variable to determine the exposure of an occupation to routine-replacing technical change. Therefore, the RTI index allows us to directly investigate the association between routinization and employment growth.

2.3 Validation of the DOT-O*NET matching

With the aim of confirming our matching choices and the reliability of the index of routine intensity defined above, we perform three checks to confirm that the switch from DOT to O*NET in the 1990-2000 decade does not lead to a systematic bias.

First, we search for marked differences between DOT and O*NET that may be attributable to our matching procedure. We did not find any systematic differences in average task scores between 1990 and 2000 (when O*NET was first introduced) compared to previous or subsequent periods (1980-1990 and 2000-2010). This is to say that, if systematic differences in the value of our task measures exist in blending DOT and O*NET, they are not necessarily due to our matching procedure. The quantile-to-quantile plots of Appendix A3 showing the distribution (by quantile) in the two considered years offers evidence in support.[8] Even when some differences exist (e.g., Cleric and Manual in Figures A3 and A4), they cancel each other out when we aggregate information for the four task measures into our routinisation index (Figure A5).

Second, the result above is further corroborated by bootstrap-based tests on the first, second, third and fourth moments of DOT (1990) and O*NET (2000) distributions for our task measures (Table

[8] The quantile-to-quantile plot reports the quantile of the variable in the left axis (RTI in t+10 in our case) in the distribution of quantiles of the variable in the right axis (RTI in t in our case). If all dots lay on the diagonal, that means that the rank distributions of the two variables are identical. This, however, does not necessarily mean that the RTI remains constant for all occupations.

A4). Notably, we only find a significant difference between the averages for clerical between 1990 and 2000 and not for math, language and manual and the RTI index. A more variegated pattern emerges for other moments of the distributions (standard deviation, skewness and kurtosis). However, when statistically significant differences are detected between 1990 and 2000, the same is found for the following decade (2000-2010) meaning that the change in the distributions of our task measures reflects a long-term pattern rather than a change that is artificially induced by our match.

Third, we compute the cross-sectional relationship between computer use at work and single items composing our task measures (Table A5).[9] Overall, in line with expectations, computer use is significantly and positively correlated with abstract tasks (MATH and LANGUAGE) and routine cognitive tasks (CLERIC), while it is significantly and negatively correlated with (routine and non-routine) manual tasks (MANUAL and NRM) and with the RTI. Importantly, the magnitude of the estimated coefficients is similar across decades. Further analyses of the relationship between technology adoption and within-occupation task shifts in section 4.1 reinforce this result.

3 The evolution of within occupation task change over four decades

Before presenting the new facts that emerge thanks to the use of a time-varying index of task change, Table 2 shows the trends in the use of human routine input in the US economy between 1980 and 2010. In this table, the evolution of the routine task intensity captures both the within- and the between-component forces. In line with previous studies, the more general index of RTI used here shows that the overall level of routinization in 2010 is substantially smaller than that of 1980 (Column 1). The decline in RTI is very limited between 1980 and 1990 (only -2.2 percent), accelerates remarkably in the 1990s (-10.7 percent) and then, consistently with Beaudry et al (2016), slows down again in the 2000s.

The significant task change that occurred in the 1990s is consistent with the historical acceleration in the diffusion of ICTs in that decade (Autor, Katz and Krueger, 1998). Looking at heterogeneous patterns across occupations, Abstract ones are the first to de-routinize in the first two decades, followed by Blue Collar and Clerical jobs in the last decade.[10] This sequence of task reconfigurations is not only consistent with models of technological revolutions in which new technologies are adopted first by high-skilled workers and then by the least skilled ones (e.g., Zeira,

[9] Computer use at work from the CPS Computer Use Supplement (October) refers to 1989 (for tasks measured in 1990), to 1997 (for tasks measured in 2000) and to 2003 (for tasks measured in 2010).

[10] For descriptive purposes, we aggregate the 322 occupations into four macro-groups that roughly illustrate the main task categories under analysis: Abstract occupations for Non-Routine Cognitive tasks; Clerks for Routine Cognitive; Blue Collar for Routine Manual; Service jobs for Non-Routine Manual. The aggregation of occupations into the four macro-groups is defined in Acemoglu and Autor (2011) while the correspondence between *OCC1990* occupations and macro-groups is based on Dorn (2009). See Table A2 in the Appendix A2.

1998; Caselli, 1999; Beaudry and Green, 2005), but it also suggests that such high-skilled workers have to learn new tasks which complement new technologies.

Changes to Abstract jobs in the third decade reveal the main limitation of our measure of routine task intensity compared to that used in related research by Atalay et al. (2018), namely that each component of the RTI index is bounded. Thereby, if an occupation had minimal level of routine intensity in 1980, a further decrease in the routine intensity cannot occur by construction. This is particularly relevant for Abstract jobs that are near the minimum of routine task intensity. To tackle this issue using our matched DOT-O*NET data, Section 4.4 explores a different measure of task change based on the idea of Deming (2017) that Abstract occupations become more complex by combining different types of non-routine tasks (e.g., social and cognitive).

Table 2 – Trends in RTI by macro-occupational group

	All Occupations	Abstract	Clerical	Blue Collar	Services
1980	0.181	-0.322	0.193	0.438	0.353
	(0.421)	(0.180)	(0.260)	(0.374)	(0.338)
1990	0.158	-0.305	0.181	0.457	0.402
	(0.438)	(0.188)	(0.276)	(0.425)	(0.320)
2000	0.051	-0.482	0.117	0.449	0.285
	(0.552)	(0.326)	(0.492)	(0.366)	(0.464)
2010	0.010	-0.333	-0.001	0.277	0.292
	(0.363)	(0.282)	(0.253)	(0.196)	(0.243)
Average	0.091	-0.367	0.117	0.408	0.325
	(0.456)	(0.273)	(0.351)	(0.361)	(0.349)

Notes: Average RTI. Weights used are the product of Census (1980; 1990; 2000) and ACS (2010) sampling weights and annual hours of labour supply

3.1 Decomposing the Long-term Changes in Routine Task Intensity

The trends shown in Table 2 pool together changes in the task content within each occupation as well as changes in the occupational composition. To gain a more precise understanding of the importance of within- vs between-occupation forces that have driven de-routinization, we decompose the overall change in RTI into three components:

$$\Delta RTI = \sum_{i,o}\left[\overline{\delta_{\iota}\phi_{\iota,o}}\Delta RTI_o + \overline{\delta_{\iota}}\Delta\phi_{i,o}\overline{RTI_o} + \Delta\delta_i\overline{\phi_{\iota o}RTI_o}\right], \quad (2)$$

where i indexes industries and o occupations. $\overline{\delta_\iota \phi_{\iota,o}} \Delta RTI_o$ represents the within-occupation component holding fixed both the within-industry $\phi_{i,o}$ and between-industry δ_i compositional changes.[11] $\overline{\delta_\iota} \Delta\phi_{i,o} \overline{RTI_o}$ is the between-occupation component and $\Delta\delta_i \overline{\phi_{\iota o} RTI_o}$ is the between-industry component.[12]

Table 3 summarizes changes in job task input by intensive (within) and extensive (between) margins. The main takeaway is that the within-occupation component explains 37 percent of the overall decline in RTI over 1980-2010, while the between-occupation accounts for 40 percent and the between-industry accounts for the remaining 23 percent. Note that the within component closely tracks the overall evolution of the RTI index as its effect is concentrated in the 1990s, explaining 2/3 of the overall change in this decade. This contrasts with the weakening in the contributions of both the within-industry, between-occupation and the between-industry components in the 1990s.

Table 3 – Decomposition of RTI

	1980-1990	1990-2000	2000-2010	1980-2010
Within occupation	0.022	-0.072	-0.011	-0.062
Total between occupation	-0.032	-0.025	-0.011	-0.067
Total between industry	-0.018	-0.010	-0.009	-0.037
Total change	-0.028	-0.107	-0.031	-0.166

Notes: Decomposition of RTI based on equation 2. Weights used are the product of Census (1980; 1990; 2000) and ACS (2010) sampling weights and annual hours of labour supply.

Spitz-Oener (2006) also finds the predominance of the within-occupation component over the between component in her study on Germany over the period 1979-1999. A recent paper by Atalay et al. (2018) also investigates changes in the task content of occupations in the US using textual data extracted from job ads published in major national newspapers. Remarkably, both studies find an acceleration in the within-occupation component in 1990s compared to the 1980s. Our analysis extends those of the aforementioned studies by also including the 2000-2010 decade, where the

[11] A preliminary sketch about the relevance of within-occupation task changes can be grasped by looking at decade-to-decade transition tables (Table B1 in Appendix B). When breaking the RTI index into quintiles, a large number of occupations lie outside the main diagonal of the transition matrix (18 percent for 1980-1990, 56 percent for 1990-2000, 48 percent for 2000-2010). This also implies that we have sufficient data variation to distinguish between the influence of the initial RTI and that of within-occupation task changes on employment dynamics.

[12] In principle, the two between components can be further decomposed to inspect the possible covariance between changes in industry and occupational structure and levels and changes in RTI. This full decomposition will read as:

$$\Delta RTI = \sum_{i,o} \left[\overline{\delta_\iota \phi_{\iota,o}} \Delta RTI_o + \overline{\delta_\iota} \Delta\phi_{i,o} RTI_o^{1980} + \Delta\delta_i \overline{\phi_{\iota o}} RTI_o^{1980} + \overline{\delta_\iota} \Delta\phi_{i,o} (\overline{RTI_o} - RTI_o^{1980}) + \Delta\delta_i \overline{\phi_{\iota o}} (\overline{RTI_o} - RTI_o^{1980}) \right]$$

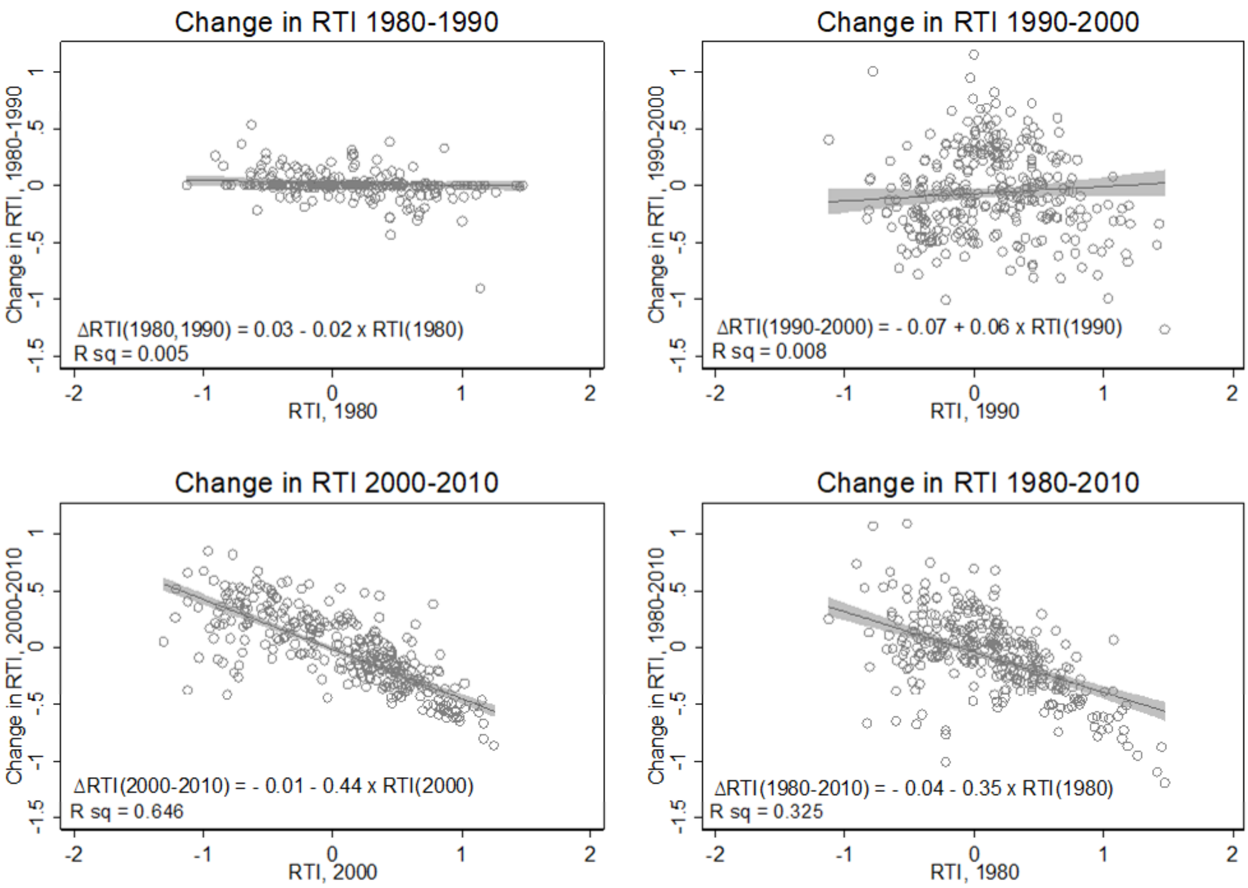
where $\overline{\delta_\iota} \Delta\phi_{i,o} RTI_o^{1980}$ and $\Delta\delta_i \overline{\phi_{\iota o}} RTI_o^{1980}$ are, respectively, the pure between-occupation and between-industry components (calculated with the initial RTI). On the other hand, $\overline{\delta_\iota} \Delta\phi_{i,o} (\overline{RTI_o} - RTI_o^{1980})$ and $\Delta\delta_i \overline{\phi_{\iota o}} (\overline{RTI_o} - RTI_o^{1980})$ represent the covariance components of, respectively, the between-occupation and between-industry components. However, the two covariance terms $\overline{\delta_\iota} \Delta\phi_{i,o} (\overline{RTI_o} - RTI_o^{1980})$ and $\Delta\delta_i \overline{\phi_{\iota o}} (\overline{RTI_o} - RTI_o^{1980})$ appear relatively small compared to the other terms, so we focus on the simpler decomposition. Details on the results of the full decomposition are available in Tables B2, B3 and B4 of the Appendix B.

significant deceleration of the within component closely matches that of de-routinization, which Beaudry et al. (2016) refer to as the "Great Reversal".

3.2 Catching-up and Heterogeneity

The scatter diagram in Figure 1 illustrates the extent to which the routine task input of each occupation changes (vertical axis) relative to each occupation's initial RTI. Consistent with the first fact, we observe significant differences across decades. The flat or even slightly increasing trends of the first two decades (top panels) contrast with a clear catching-up pattern of the 2000s (bottom, left-hand panel). Therein, the decrease in routine task intensity is larger among jobs that had a higher RTI at the beginning of the period. On the whole, the pattern of the 2000s clearly dominates the overall change (bottom, right-hand side panel). Compared to the 1990s, where the distribution of routine task intensity to new technologies becomes slightly more dispersed, the 2000s are characterized by substantial redistribution of non-routine intensive tasks to low- and medium-skilled occupations.

Figure 1 – Catching up of RTI across occupations (*OCC1990*)



Notes: Weights used in regressions are the product of Census (1980; 1990; 2000) and ACS (2010) sampling weights and annual hours of labour supply.

Table 4 replicates the decomposition of routinization index by macro occupational groups (Abstract, Clerical, Blue-collar and Service occupations) and the two macro-sectors (non-manufacturing and manufacturing). Consistent with this, the de-routinization pattern highlighted in Table 2 is driven by a task reorientation that primarily occurred in Clerical and Blue-collar occupations. For Clerical occupations, the decline in the RTI is constant over time, while for Blue-collar occupations, it is more pronounced in the last decade.

A recurrent pattern in our data is that, during the first wave of ICTs in the 1990s, the strongest change was the decline of RTI among Abstract occupations. In the 2000s, high-skill Abstract occupations become more routine intensive over time, again in line with the Great Reversal hypothesis (Beaudry et al., 2016). Re-routinization of Abstract occupations may reveal the greater capacity of machines in performing tasks such as translating complex documents, writing reports and legal briefs, as well as diagnosing diseases (Brynjolfsson and McAfee, 2014), or simply a limitation of our measures for these occupations, which will be addressed in Section 4.4.

Table 4 – Decomposition of RTI by decade and occupational group

	1980-1990	1990-2000	2000-2010	1980-2010
	Abstract			
Within occupation	0.026	-0.175	0.140	-0.009
Total between occupation	-0.002	-0.004	-0.004	-0.010
Total between industry	-0.002	0.003	0.009	0.010
Total change	0.022	-0.176	0.145	-0.009
	Clerical			
Within occupation	0.012	-0.050	-0.075	-0.113
Total between occupation	-0.031	-0.031	-0.006	-0.068
Total between industry	-0.007	-0.001	-0.001	-0.009
Total change	-0.026	-0.082	-0.082	-0.190
	Blue collar			
Within occupation	0.010	0.026	-0.170	-0.134
Total between occupation	0.005	-0.011	0.013	0.006
Total between industry	-0.002	-0.009	-0.001	-0.011
Total change	0.013	0.006	-0.158	-0.139
	Service			
Within occupation	0.068	-0.081	0.018	0.004
Total between occupation	-0.009	-0.023	0.009	-0.023
Total between industry	-0.005	-0.014	-0.001	-0.020
Total change	0.054	-0.118	0.026	-0.038

Notes: Decomposition of RTI based on equation 2. Macro-occupational groups defined in Table A3. Weights used are the product of Census (1980; 1990; 2000) and ACS (2010) sampling weights and annual hours of labour supply

When considering different industries (Table 5), we observe that the decline in the RTI is larger in manufacturing than in non-manufacturing industries. Moreover, for manufacturing industries the within-occupation change contributes to more than half (51 percent) of the total decline in RTI, while it only accounts for 38 percent of the decline in RTI in non-manufacturing sectors. Importantly, the within-occupation component is relatively more important in non-manufacturing sectors (the 1990s) than in manufacturing sectors (the 2000s). This is consistent with the fact that the first wave of ICTs replaced clerical tasks in service sectors, while the second wave in the 2000s pertained to the automation of manual tasks in manufacturing (Brynjolfsson and McAfee, 2014). Together with the differential decadal patterns across occupations, we interpret this finding as supporting our measure of within-task occupational changes and its ability to closely mimic well-established facts on the diffusion of ICTs and automation.[13]

Table 5 – Decomposition of RTI by decade and industry

	1980-1990	1990-2000	2000-2010	1980-2010
	Manufacturing industries			
Within occupation	0.004	-0.054	-0.088	-0.138
Total between occupation	-0.048	-0.032	-0.031	-0.111
Total between industry	-0.012	0.003	-0.012	-0.021
Total change	-0.054	-0.083	-0.131	-0.270
	Non-manufacturing industries			
Within occupation	0.027	-0.076	0.003	-0.046
Total between occupation	-0.027	-0.023	-0.007	-0.057
Total between industry	-0.009	-0.008	-0.003	-0.012
Total change	-0.009	-0.107	-0.007	-0.123

Notes: Decomposition of RTI based on equation 2. Weights used are the product of Census (1980; 1990; 2000) and ACS (2010) sampling weights and annual hours of labour supply.

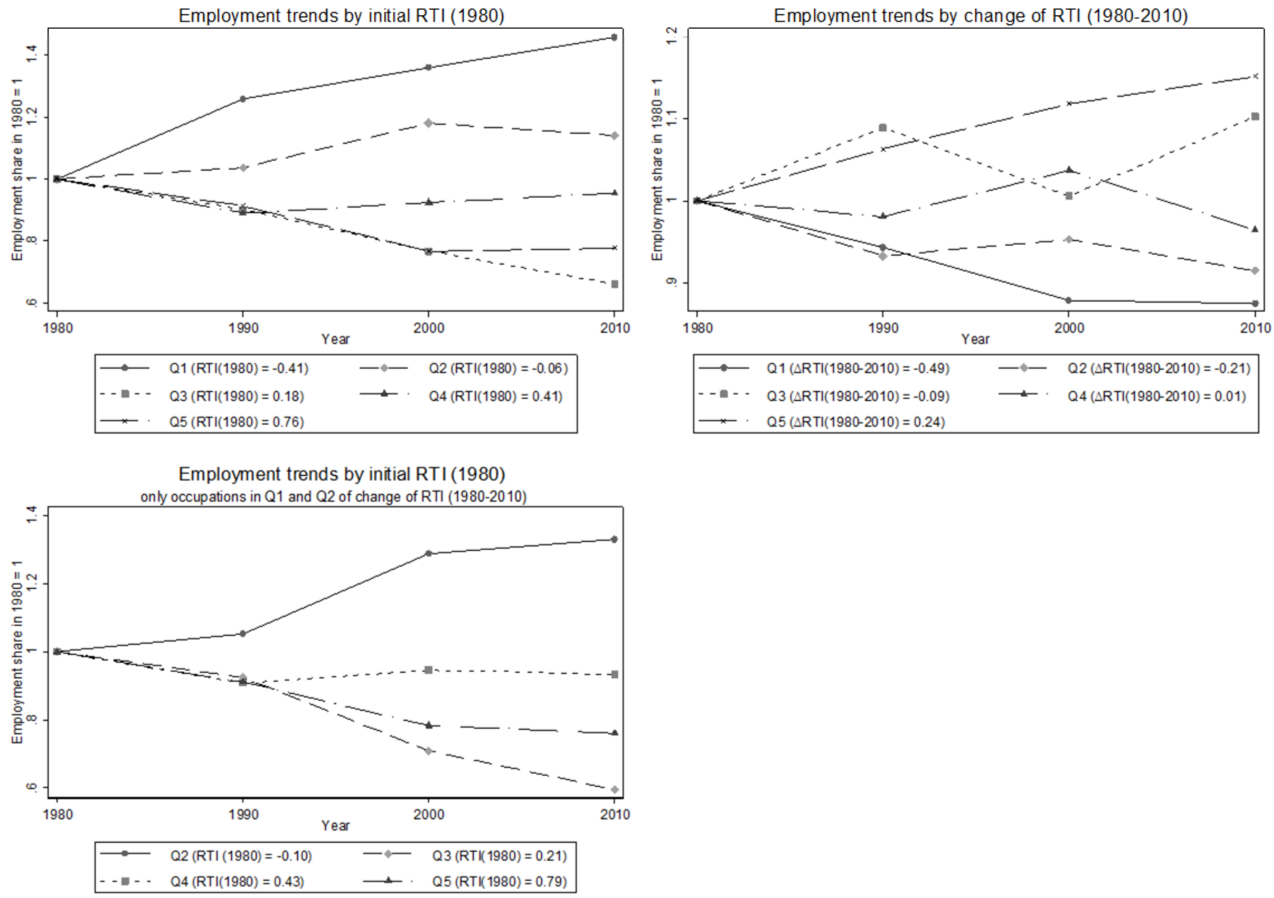
3.3 A First Glance at Employment Dynamics

A key objective of the present study is to assess the relationship between qualitative change in the task content of occupations and changes in labour demand. To this end, we unpack aggregate trends of full-time US employees over the period 1980-2010 by partitioning the labour force into quintiles of initial RTI. In Figure 2, the employment share of all groups is set to 1 in 1980 so that subsequent points in the diagram depict the mean employment of each group of occupations over time. The first diagram of Figure 2 (top, left-hand side) shows changes in employment by quintiles of initial values of RTI. Here, a divide emerges between occupations that made less intensive use of routine tasks in the 1980, which experienced substantial increase in labour demand, and those with a stronger

[13] Notice that considering only the between-occupations component will underestimate the shift away from routine tasks. Moreover, the between-occupations component varies less across decades.

routine bias. This is the familiar polarization pattern seen in prior empirical literature (ALM, 2003; Spitz-Oener, 2006; Deming and Kahn, 2018), showing that high initial routine intensity carries a penalty in terms of employment prospects.

Figure 2 – Trend in employment share by initial quintile of RTI or Δ RTI



Notes: Trends in the annual hours of labour supply multiplied by sampling weights by groups of occupations defined as quintiles of the weighted distribution of RTI (1980, top-left and bottom-left panels) and of RTI change (1980-2010, top-right and bottom-left panels).

The second diagram of Figure 2 (top, right-hand side) shows changes in employment by quintiles of within-occupational changes in RTI. Here we observe that occupations that de-routinize the most (Q1 and Q2) have worse employment performance throughout the period. But this of course does not account for the initial level of RTI. In Figure 3, we unpack the trends of the sub-group of occupations that de-routinize the most, i.e., the first and second quantile in terms of change in routine task intensity, controlling for the initial level of RTI. Interestingly, we find that occupations that de-routinize the most are highly polarized in terms of long-term employment patterns. Among those that are highly routine intensive (Q5 and Q4) we observe a large employment decline, while among those with a relatively low initial routine intensity (Q2[14]) we observe a large employment increase. That is, among the occupations that substantially de-routinize, only those that are initially

[14] Because our measure of RTI is bounded, occupations in the first quantile of routine task intensity cannot be among in the first two quintiles of de-routinization.

less routine escape the employment decline.

Taken together, these stylized facts indicate that accounting for within-occupation changes in task content yields a complex picture of structural changes in US labour markets. These issues will be explored in a more rigorous way in the next section with the aid of multivariate regressions to shed light on the conditional correlation between de-routinization and employment growth.

4 Drivers and implications of within-occupation task changes

Tasks are the interface of the race between technology and education (Goldin and Katz, 2007; Acemoglu and Autor, 2011). On the one hand, new technologies may entail a radical reallocation in the share and type of tasks performed by humans, and this can occur along both the intensive (within-occupation) and the extensive (between-occupation) margin. On the other hand, where the intensive margin is relevant, educational programmes need to adapt to keep pace with changes in the demand for specific tasks within affected occupations (Vona and Consoli, 2015). As clerical jobs, such as clerks and assistants, have experienced substantial task reconfiguration towards organizational skills and non-routine tasks (ΔRTI = -0.19 over the three decades), a concurrent change in educational opportunities is necessary to equip workers with skills that are less exposed to the risks of technology. We expect that the diffusion of technology, such as ICTs, is the primary driver of within-occupation task shifts, and that those shifts are correlated with changes in the educational requirements. By testing these two predictions, the first two parts of this section closely follow related papers on within-occupation task reconfigurations (ALM, 2003; Spitz-Oener, 2006).

The third and main part of this section explores the correlation between within-occupation task shifts and outcomes of the race between technology and education, namely employment growth.[15] Notice that task changes can be interpreted as a proxy of the degree of adaptation to structural transformations. Theory on routine-replacing technological change, such as the Ricardian model of Acemoglu and Autor (2011) and especially the recent extension with endogenous technical change

[15] We focus on employment growth rather than wage growth for three reasons. First, while changes in the employment structure, such as employment polarization, have been particularly pronounced both in the US and in Europe (Goos et al., 2009; 2014), the polarization of the wage structure predicted by the task model appears less general than that of employment (Naticchioni et al., 2014). This can be explained by cross-country differences either in institutions (e.g., Blau and Kahn, 1996) or in skill levels (e.g., Leuven et al., 2004). Therefore, we are more confident regarding the generality of our analysis for employment than for wages. Second, we can directly contribute to the literature on the reversal in the demand of abstract tasks in the 2000s (Beaudry et al., 2016), using a more general task measure. Our analysis revisits the Great Reversal using a time-varying measure of exposure to routinization. Third, a fully-fledged analysis of wages would require a transition to individual-level data, possibly in panel, to address the issue of selection of workers into occupations. The recent study of Ross (2017b) shows that reorientation towards non-routine tasks is beneficial for wages controlling for individual fixed effects. By focusing on inequality, Atalay et al. (2017) show that within-occupation changes in task content of occupations since the 1960s account for the largest component of the increase in earnings inequality. Our analysis complements these findings by measuring the association between task changes and employment growth.

of Acemoglu and Restrepo (2017), clearly advocates that successful adaptation should entail a reorientation away from routine tasks. Accordingly, occupations that de-routinize faster are expected to experience faster growth in wages and employment shares.

4.1 Technological change and within-occupation task changes

We examine the association between within-occupation task shifts and a proxy of technological change in the workplace: the change in the share of workers using computers. Although we are aware of the limitations of this measure, it is the only occupation-level measure for which data are available and that has been used in previous studies (e.g., Autor, Katz and Krueger, 1998). As information on computer use at work by occupations from CPS (Current Population Survey) is only available for few selected samples, we focus our analysis on the 1990-2000 decade.[16] This is critical for our study given the data compatibility issues raised by the combination of DOT and O*NET. Similarly, within-occupation task changes occurred mostly in this decade, which further reinforces our focus on this decade.[17] We use a long-difference estimator to retrieve the associations between the change in the task content of occupation and the change in computer use, controlling for the initial levels of task input and computer use:

$$\Delta Task_o^{1990-2000} = \alpha + \beta Task_o^{1990} + \gamma Computer\ use_o^{1989} + \delta \Delta Computer\ use_o^{1989-1997} + \varepsilon_o \quad (3)$$

Also, this analysis represents a further robustness check of choice of task items for the match between DOT and O*NET. For this reason, and in contrast to subsequent analyses where we focus on the aggregate routine-task intensity index, we present the correlations for the four task items that enter the RTI index, the non-routine manual task measure and the RTI index itself.

Table 6 reports the results of this analysis. In line with the existing literature (ALM, 2003; Spitz-Oener, 2006), we find a positive contribution of the change in computer use to the within-occupation change in analytical (math) and interactive (language) tasks, a negative contribution to the change in routine (manual and clerical) and no clear effect on non-routine manual tasks (NRM, see Table A1 for details on the NRM measure). By combining these results, we find a negative association between the change in computer use and the change in routine-task intensity. Note that the increase in the share of workers using computers at work was 14.3% during this decade. This implies an average change in RTI that is 1.6 times the actual change (-0.094 vs. -0.058). Although

[16] More specifically, information on computer use at work is available for CPS Computer Use Supplement (October) for years 1989, 1993, 1997, 2001 and 2003.

[17] We measure computer use as the share of workers that use a computer at work in an occupation. We use 1997 as a proxy for computer use in 2000 as we expect computer use to affect tasks with a lag. However, results are qualitatively unaffected if we use computer use in 2003 to proxy the 2000 values.

this may appear surprisingly large, it is in line with the estimates by ALM (2003; for the period 1984-1997 computerization more than fully accounts for the observed changes in single task measure) and Spitz-Oener (2006; effects ranging between 47% (non-routine interactive) and 90% (routine cognitive) that combined together in a RTI index will deliver an association of a similar size).

Table 6 –Technological change and within-occupation task changes

	(1)	(2)	(3)	(4)	(6)	(5)
Growth 1990-2000	Math	Language	Cleric	Manual	NRM	RTI
Task intensity in 1990	-0.436***	-0.389***	0.022	-0.238**	-0.646***	-0.050
	(0.070)	(0.063)	(0.149)	(0.102)	(0.136)	(0.128)
Computer use in 1989	0.162**	0.096	-0.013	-0.263***	-0.108	-0.068
	(0.081)	(0.086)	(0.122)	(0.061)	(0.068)	(0.255)
Growth in computer use (1989-1997)	0.146*	0.384***	-0.335	-0.429***	-0.101	-0.654**
	(0.078)	(0.128)	(0.219)	(0.117)	(0.103)	(0.292)
R squared	0.327	0.209	0.0327	0.290	0.320	0.0392

Notes: N=322 occupations. OLS regression. Weights used are the product of CPS Computer Use Supplement (October) sampling weights and annual hours of labour supply. Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Computer use measured as the share of workers in the occupation that use computers on the job (source: CPS Computer Use Supplement October 1989, 1997). As a proxy for non-routine manual task intensity we use the DOT item EYEHAND (Eye-hand-foot coordination), that is measured over a range 1-5. This task is matched to the O*NET task 'Response orientation' (1.A.2.b.3, importance). See Table A1.

Overall, our data-set built from the combination of DOT and O*NET confirms the strong association between computer use and task reconfiguration within an occupation. In light of this, we can safely attribute the bulk of this reconfiguration to routine-replacing technological change.

4.2 Within-occupation task changes and educational requirements

How did education respond to the technology-driven task shifts reported above? Decreasing routine task intensity parallels increasing task complexity and thus is expected to be positively correlated with skill upgrading. Slow or no adaptation of education and training can only exacerbate skill gaps (Vona and Consoli, 2015) and the associated negative labour market outcomes (Guvenen et al, 2019). To this end, again following ALM (2003) and Spitz-Oener (2006), we predict changes in educational requirements associated with within-occupation task reconfigurations. In practice, we first estimate the following equation, weighted by the hours worked:

$$Educ_{o,t} = \alpha + \beta_t RTI_{o,t} + \delta_t + \varepsilon_{o,t} \tag{4}$$

and then compute the average predicted increase in education due to changes in the RTI index as: $\Delta \widehat{Educ}_t = \sum_o h_{o,t} \times (\hat{\beta}_t \Delta RTI_{o,t})$, where $Educ_{o,t}$ and $h_{o,t}$ are, respectively, a measure of educational level and of the hours worked by occupation o at time t.

A novelty of the present study is that, besides standard measures of skill upgrading such as the share of graduates working a specific occupation, we use data on the Classification of Instructional Program (CIP). These provide, for the entire timespan under analysis, an accurate description of the number and the types of instructional programmes that are required to perform the set of tasks of a given occupation. A key advantage of CIP data is that they are organized by SOC code and thus can be easily matched with our original data (see the Appendix C for details). We use CIP data to construct three variables: total number of instructional programmes (a proxy of educational complexity), shares of business-oriented programmes and technical-oriented programmes. We manually classify programmes into business- and technical-orientated to capture adjustments in education, and thus to match changes in the demand of the two main components of non-routine tasks: interactive and analytical.

Table 7 – Quantification of education

	Average value in 1980	Increase predicted by changes in the task content	Actual increase	R squared in the education regression	F-test of joint significance of RTI and its interaction with time dummies
Share of workers with a high school degree	0.354	-0.019	-0.033	0.452	46.05***
Share of workers with a college degree	0.313	0.030	0.085	0.534	123.60***
Share of workers with a post-graduate degree	0.108	0.013	0.023	0.266	40.76***
Number of instructional programmes	2.582	3.397	4.048	0.359	9.01***
Share of 'business' instructional programmes	0.284	0.019	0.018	0.136	22.86***
Share of 'technical' instructional programmes	0.091	0.003	0.013	0.016	1.95

Notes: Average values. Weights used are the product of Census (1980; 1990; 2000) and ACS (2010) sampling weights and annual hours of labour supply. Educational attainment (high-school, college, post-graduate) is retrieved from individual worker data from IPUMS (decennial Census for 1980, 1990 and 2000; ACS for 2010). The number and the composition of educational programmes is retrieved from the Classification of Instructional Programs (CIP; see Appendix C). Regression results are reported in Table C2 in Appendix C.

Table 7 confronts the predicted changes in education by within-occupation task changes with the actual ones, while the full set of results is given in Table C2 of the Appendix C. As regards the standard measures of education, task reconfigurations predict a statistically significant (as shown by F-tests in column 5) portion of the skill upgrading of the US workplace over the three decades of our analysis. By considering all observed trends of occupational (de-)routinization, our model captures 58% of the decline in the share of high-school graduates, one-third of the increase in the share of college graduates and a remarkable 56% of the increase in the share of post-graduates.

With regards to the change in the number and type of educational programmes, the association between RTI and skill upgrading is statistically significant for the total number of instructional programmes (in log) and the share of business-related programmes, but not for the share of technical programmes. This resonates with the finding of Deming (2017) that the bulk of the shift towards non-routine tasks has been towards non-routine interactive tasks, such as social and managerial ones, performed by graduate students in business-related disciplines. Remarkably, within-occupation task changes predict the entire increase in the share of business instructional programmes and 84% of the general increase in educational complexity as measured by the total number of programmes required to perform a certain job. This suggests that adjustments in the educational supply are important, not only along the extensive margin, i.e., increasing the share of college graduates, but also along the intensive margin by increasing the variety and the type of educational programmes required to perform a job (Vona and Consoli, 2015).

4.3 Implications of within-occupation task changes for long-term employment growth

We retrieve the conditional association between decennial employment growth and task reconfiguration by estimating the following equation:

$$\Delta ln(L_{oi,t}) = \alpha + \beta_1 RTI_{o,t-1} + \beta_2 \Delta RTI_{o,t} + \gamma NRM_{o,t-1} + \varphi OFF_o + \delta_t + \delta_i + \varepsilon_{o,t} \qquad (5)$$

where the decennial (or the thirty year) change in the log of employment of occupation o in industry ($L_{oi,t}$) is regressed on three lagged measures of occupational task orientation at the beginning of the period: i) $RTI_{o,t-1}$, the initial value of routine intensity; ii) OFF_o, a time-invariant index of offshorability as defined in Acemoglu and Autor (2011), iii) $NRM_{o,t-1}$, non-routine manual intensity, as well as industry and year dummies. Controlling for offshorability and NRM is the most obvious and direct way to isolate the incidence of routinization from that of other intervening factors at the occupation-level. Our variable of interest is the long-term change in routine task intensity within an occupation, $\Delta RTI_{o,t}$.

Similar to Goos et al. (2014), estimates are performed at the occupation-by-industry level to control, in a flexible way, for industry-level drivers such as globalization, which may influence employment dynamics. As a variant of the long-term 30-year model, we also estimate equation 5 where all decades are stacked together.[18] Finally, all estimates are weighted for the hours worked at the beginning of the period and the standard errors are clustered at the occupation-level

An obvious caveat is that the coefficients of our main variable of interest, ΔRTI, cannot be interpreted as a causal effect, although the sources of estimation bias are likely to offset each other. On the one hand, self-selection of more skilled workers into occupations that de-routinize faster makes these occupations more productive and less likely to experience a decline, bringing an upward bias in the estimated coefficient of ΔRTI. On the other hand, the fact that the changes in RTI are bounded from above underestimates the effective task reorientation for top occupations. Since abstract occupations are becoming more complex and are also the main 'winners' in terms of earnings and employment growth (Deming, 2017), this leads to an underestimation of the true effect of task shifts on employment.

Results are shown in Table 8. For comparison with previous studies (e.g., Goos et al., 2014), panel A presents estimates of equation 5 without our main variable of interest, ΔRTI. Clearly, routine-task intensity is associated with employment growth for all the decades, but, consistent with the hypothesised Great Reversal (Beaudry et al., 2016), the size of this association fades over time.

In panel B, we include the change in routine task intensity as the explanatory variable. The most important finding is that within-occupation changes in routine task intensity have a statistically significant association with employment dynamics over the entire 30-year span of our analysis (columns 4-5). However, the effect is concentrated in the decade 1990-2000 (column 3).[19] In this crucial transition for US labour markets, as also pointed out by Atalay et al. (2018), occupations that experienced a relatively larger decrease in routine task intensity grew faster than occupations with a similar level of initial routine task intensity. Importantly, the inclusion of our proxy of within-occupation task change reduces the size of the coefficient of initial routine task intensity, which becomes statistically insignificant in the last decade.

[18] In the stacked model, we slightly amend the specification of equation 5 by interacting industry dummies and offshorability, which is time-invariant, with time dummies.

[19] Tables D1, D2 and D3 in Appendix D show that the results are robust using the time-invariant weights from the April 1971 CPS Monthly File, including non-routine manual tasks in the RTI index and using a more parsimonious specification without the task measures for offshorability and for the importance of non-routine manual tasks.

Table 8 – Baseline estimates

Panel A - Only initial RTI					
Dep: Δlog(Empl)	1980-1990	1990-2000	2000-2010	1980-2010	1980-2010 stacked
Initial RTI	-0.223***	-0.139**	-0.077**	-0.474***	-0.129***
	(0.054)	(0.059)	(0.039)	(0.117)	(0.029)
Offshorability	0.727**	-0.411	0.069	0.736	0.732**
	(0.363)	(0.401)	(0.199)	(0.693)	(0.313)
Initial man task	0.274	0.081	0.058	0.571	0.141
	(0.183)	(0.267)	(0.099)	(0.395)	(0.125)
R sq	0.317	0.179	0.380	0.365	0.262
N	29847	28897	28083	26531	86827
Panel B - Initial and change of RTI					
Dep: Δlog(Empl)	1980-1990	1990-2000	2000-2010	1980-2010	1980-2010 stacked
Initial RTI	-0.216***	-0.119**	-0.055	-0.627***	-0.158***
	(0.058)	(0.058)	(0.054)	(0.126)	(0.039)
ΔRTI	0.239	-0.237**	0.047	-0.426**	-0.138**
	(0.241)	(0.103)	(0.085)	(0.207)	(0.067)
Offshorability	0.763**	-0.565	0.095	0.405	0.679**
	(0.364)	(0.411)	(0.206)	(0.736)	(0.313)
Initial man task	0.272	0.071	0.056	0.617	0.136
	(0.182)	(0.260)	(0.100)	(0.378)	(0.125)
R sq	0.319	0.187	0.381	0.370	0.264
N	29847	28897	28083	26531	86827

Notes: OLS model. All models include industry dummies. Weights used are the start of period product of Census (1980; 1990; 2000) sampling weights and annual hours of labour supply. Robust standard errors clustered at occupation level in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. In the stacked differences specification offshorability (unreported) and industry dummies are interacted with period dummies.

The magnitude of the association between our variables of interest and employment growth is quantified in Table 9. Since both ΔRTI and RTI have no clear scale, we quantify the change in employment implied by inter-quartile changes in our variables of interest. The goal is to compare the extent to which previous estimates, which consider only the role of initial routine-task intensity, fail to account for the overall association between routine-replacing technological change and employment. As expected given the boundedness of ΔRTI for Abstract jobs, differences in the initial level of RTI explain a larger portion of employment growth than changes in routine-task intensity. To illustrate, over the thirty years under analysis (e.g., row 4), occupations in the bottom quartile of routine task intensity grow on average 41% more than occupations in the top quartile. In turn, the long-term inter-quartile difference in the change of routine task intensity accounts for a lower bound with a 10.8% difference (row 5) to an upper bound with a 15.8% difference (row 4) in employment growth. However, the magnitude of the association between task reorientation and employment growth is larger than that of the initial RTI in the 1990s.

Table 9 – Quantification of employment changes

	IQR initial RTI	IQR ΔRTI	Predicted employment change (percentage) by 1 IQR decrease of initial RTI	Predicted employment change (percentage) by 1 IQR decrease of ΔRTI
1980-1990	0.651	0.046	0.141	*-0.011*
1990-2000	0.730	0.428	0.087	0.101
2000-2010	0.939	0.420	*0.052*	*-0.020*
Long difference 1980-2010	0.797	0.354	0.408	0.158
Stacked 1980-2010	0.651	0.252	0.428	0.108

Notes: The quantification is based on baseline results from Panel B of Table 8. Not significant effects (p-value<0.1) are indicated in italics.

To summarize, explicitly accounting for within-occupation task changes does not radically alter the main findings of the existing literature on routine-replacing technological change but adds to it by uncovering important nuances that have thus far been neglected. The association between employment and changes in the task content of occupations during the first wave of the ICT revolution in the 1990s calls for adaptation in the educational supply to fill the skill-task gap opened by the new technological regime. The subsequent decline in the importance of within-occupation task changes may be either an indication of successful catching-up of education with technology, or simply of a slowdown of technological change in the spirit of previous studies (e.g., Beaudry et al., 2016). Our study is inconclusive in discriminating among these competing explanations, but points to a new, empirically testable, direction for future research.

4.4 Heterogeneous effects by occupational groups and macro-sectors

This final section replicates the estimation of equation 5 splitting the sample by macro occupational groups. At the cost of significantly decreasing the source of variation used to identify the association between employment growth and routinization, we seek to discern which occupations have benefited the most from changes in task content. The results in Table 10 broadly support the findings of the descriptive section, namely that within-occupation task changes are particularly important in explaining employment patterns of Clerical and Blue-collar occupations. Notice that, as expected, reducing the source of data variation used for our estimation entails that the coefficients of both ΔRTI and RTI are imprecisely estimated.

Table 10 – Estimates by macro-occupational group

Abstract					
Dep: Δlog(Empl)	1980-1990	1990-2000	2000-2010	1980-2010	1980-2010 stacked
Initial RTI	-0.020	0.203	-0.106**	-0.461	-0.009
	(0.183)	(0.245)	(0.043)	(0.415)	(0.075)
ΔRTI	0.372	0.163	0.045	0.082	0.137
	(0.525)	(0.213)	(0.053)	(0.285)	(0.102)
R sq	0.414	0.277	0.418	0.451	0.351
N	8164	8183	8406	7589	24753
Clerical					
Dep: Δlog(Empl)	1980-1990	1990-2000	2000-2010	1980-2010	1980-2010 stacked
Initial RTI	-0.439*	-0.091	0.112	-1.186***	-0.200**
	(0.218)	(0.169)	(0.102)	(0.320)	(0.088)
ΔRTI	-0.786	-0.258	0.400***	-0.751**	-0.119
	(0.689)	(0.224)	(0.130)	(0.342)	(0.116)
R sq	0.346	0.434	0.419	0.461	0.414
N	6522	6234	6022	6042	18778
Blue-collar					
Dep: Δlog(Empl)	1980-1990	1990-2000	2000-2010	1980-2010	1980-2010 stacked
Initial RTI	-0.196*	-0.151	0.162	0.200	-0.064
	(0.096)	(0.114)	(0.105)	(0.323)	(0.068)
ΔRTI	0.470***	-0.206	-0.003	0.151	-0.165*
	(0.136)	(0.122)	(0.143)	(0.419)	(0.089)
R sq	0.314	0.264	0.383	0.366	0.298
N	12301	11656	10696	10295	34653
Service					
Dep: Δlog(Empl)	1980-1990	1990-2000	2000-2010	1980-2010	1980-2010 stacked
Initial RTI	-0.188	-0.198	0.157***	-0.463*	-0.067
	(0.239)	(0.159)	(0.035)	(0.256)	(0.082)
ΔRTI	-0.460	-0.116	0.184***	-0.302	-0.130
	(0.721)	(0.089)	(0.055)	(0.246)	(0.104)
R sq	0.548	0.354	0.579	0.595	0.483
N	2732	2680	2714	2480	8126

Notes: OLS model. Robust standard errors clustered at occupation level are in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. All models include industry dummies. Weights used are the start of period product of Census (1980; 1990; 2000) sampling weights and annual hours of labour supply. Results for offshorability and manual task intensity are not reported. In the stacked differences specification offshorability and industry dummies are interacted with period dummies.

Table 11 shows the estimates of equation 5 splitting our sample by the two macro-sectors: manufacturing and non-manufacturing. In both cases, employment grows relatively faster in occupations that become relatively less-routine intensive. However, the two macro-sectors diverge in the last decade. While the association between occupational de-routinization and employment growth remains positive, large and statistically significant for manufacturing, it is no longer significant for the rest of the economy. Remarkably, the association between employment growth and the initial level of routine-task intensity follows the same pattern. These findings resonate with current trends in the literature that link recent advances in technology and the rapid diffusion of robots that will primarily substitute the motorial and physical tasks that are intensively used in manufacturing (Graetz and Micheals, 2018; Acemoglu and Restrepo 2018).

Table 11– Results by macro-sector

Panel A - Manufacturing					
Dep: Δlog(Empl)	1980-1990	1990-2000	2000-2010	1980-2010	1980-2010 stacked
Initial RTI	-0.306***	-0.169**	-0.209**	-0.840***	-0.221***
	(0.059)	(0.075)	(0.084)	(0.207)	(0.048)
ΔRTI	0.722***	-0.273**	-0.260**	-0.687*	-0.226**
	(0.169)	(0.134)	(0.126)	(0.369)	(0.091)
R sq	0.405	0.219	0.344	0.280	0.300
N	11700	10881	10237	9928	32818
Panel B - Non-manufacturing					
Dep: Δlog(Empl)	1980-1990	1990-2000	2000-2010	1980-2010	1980-2010 stacked
Initial RTI	-0.177**	-0.093	-0.027	-0.537***	-0.134**
	(0.085)	(0.071)	(0.052)	(0.156)	(0.052)
ΔRTI	0.110	-0.231*	0.107	-0.387*	-0.113
	(0.292)	(0.123)	(0.084)	(0.222)	(0.077)
R sq	0.242	0.167	0.288	0.292	0.214
N	18147	18016	17846	16603	54009

Notes: OLS model. Robust standard errors clustered at occupation level in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. All models include industry dummies. Weights used are the start of period product of Census (1980; 1990; 2000) sampling weights and annual hours of labour supply. Results for offshorability and manual task intensity are not reported. In the stacked differences specification offshorability and industry dummies are interacted with period dummies.

Finally, because task reconfigurations have an upper bound, the role of within-occupation task shifts is underestimated for occupations, i.e., Abstract jobs, with high initial levels of task complexity. To deal with this issue, we re-estimate equation 5 by including a measure of task variety that is described in Appendix A1. Results are summarized in Table 12 where, for the sake of brevity, we focus on the comparison between Abstract occupations and all other occupations. The main finding is that increasing task variety is positively associated with employment growth within the group of abstract jobs, but not all for the other occupations. This is suggestive of a different margin of task reorientation for already complex occupations. Rather than merely requiring a more intensive use of non-routine tasks, such occupations adapt by increasing task variety (Acemoglu and Restrepo, 2017), multi-tasking (Goerlich and Snower, 2013) and cognitive-social task complementarities (Deming, 2017). Obviously, the insights given by the present study on the different margins of task reorientation require further validation in the context of a homogeneous dataset, such as O*NET when a sufficient timespan will be available.

Table 12– Estimates that account for the variety in tasks

Panel A - Abstract occupations					
Dep: Δlog(Empl)	1980-1990	1990-2000	2000-2010	1980-2010	1980-2010 stacked
Initial RTI	0.041	0.234	-0.138**	-0.297	-0.055
	(0.180)	(0.225)	(0.056)	(0.435)	(0.084)
ΔRTI	0.285	0.202	0.109	0.010	0.186
	(0.424)	(0.268)	(0.072)	(0.275)	(0.131)
Δ Variety Routine	-0.041	0.001	-0.049*	0.051	-0.026
	(0.063)	(0.037)	(0.026)	(0.044)	(0.023)
Δ Variety Non-Routine	0.102*	0.075*	0.012	-0.008	0.035**
	(0.049)	(0.042)	(0.012)	(0.062)	(0.016)
R sq	0.425	0.288	0.425	0.454	0.356
N	8164	8183	8406	7589	24753
Panel B - All occupations					
Dep: Δlog(Empl)	1980-1990	1990-2000	2000-2010	1980-2010	1980-2010 stacked
Initial RTI	-0.167***	-0.138**	-0.051	-0.641***	-0.163***
	(0.047)	(0.058)	(0.053)	(0.136)	(0.040)
ΔRTI	0.476***	-0.230**	0.065	-0.539**	-0.128*
	(0.156)	(0.101)	(0.082)	(0.230)	(0.069)
Δ Variety Routine	-0.038	0.007	-0.019	-0.020	-0.010
	(0.055)	(0.021)	(0.012)	(0.037)	(0.012)
Δ Variety Non-Routine	0.071	0.013	-0.005	-0.066*	0.012
	(0.048)	(0.023)	(0.007)	(0.039)	(0.009)
R sq	0.329	0.187	0.383	0.376	0.265
N	29847	28897	28083	26531	86827

Notes: OLS model. Robust standard errors clustered at occupation level in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. All models include industry dummies. Weights used are the start of period product of Census (1980; 1990; 2000) sampling weights and annual hours of labour supply. Results for offshorability and manual task intensity are not reported. In the stacked differences specification offshorability and industry dummies are interacted with period dummies.

5 Concluding remarks

This paper has presented an analysis of occupational task content over the period 1980-2010 in the US. We fill a gap in the empirical literature on structural changes in labour markets by adding an important nuance to the extended literature that mostly focusses on the reallocation of employment between occupations at the extensive margin.

Looking at changes in job tasks within occupations, at the intensive margin, affords the opportunity to account for the disruptive effects of new technology beyond a short-term horizon, and to capture the qualitative transformation of work activities and, thus, of the necessary skills. Moreover, an analysis of how the job content changes over time opens up new avenues towards informing the design of education and training. To this end, we implemented a procedure to match the main sources of occupation-specific data, DOT and O*NET. This allowed us to create a consistent index of within-occupation routine task intensity over a thirty-year period, and to reassess the long-term structural changes in the US labour market during the momentous era of widespread adoption of automation.

Descriptive evidence shows that within-occupation task change accounts for more than one third of the overall decline in RTI between 1980 and 2010. Beneath this aggregate pattern, however, stand important nuances. First, the within-component task change accelerates in the 1990s and decelerates in the 2000s. Second, the acceleration in the 1990s is accompanied by a divergence in the routine-intensity of jobs, with abstract occupations becoming less routine intensive. By contrast, the deceleration of the 2000s is accompanied by a substantial de-routinization of Clerical and Blue-collar occupations with respect to Abstract occupations. The regression analysis yields three main findings. First, as expected, change in computer use exhibits a positive association with within-occupation changes in analytical and interactive tasks and a negative association with changes in routine tasks. Second, within-occupation task changes predict a statistically significant proportion of the educational expansion, both in terms of graduate and post-graduate education and in the number and type of educational programmes supplied. Third, changes in RTI have a significant influence on employment growth over the entire timespan. Conditional on the initial routine task intensity, a task reorientation towards non-routine tasks allows one to escape employment decline, especially in 1990-2000 and among Clerical occupations.

References

Acemoglu, D. and Autor, D.H. (2011) Skills, tasks and technologies: Implications for employment and earnings. In: Ashenfelter, O., and Card, D. (Eds.) Handbook of labor economics. Elsevier. Chap. 12, 1043–1171.

Acemoglu, D. and Restrepo, P. (2017) The Race Between Man and Machine: Implications of Technology for Growth, Factor Shares and Employment. American Economic Review (forthcoming).

Atalay, E., Phongthiengtham, P., Sotelo, S., and Tannenbaum, D. (2017) The evolving US occupational structure. Mimeo.

Autor, D.H. (2013) The task-approach to labor markets: an overview. Journal of Labor Market Research 46(3), 185-199.

Autor, D.H., Levy, F. and Murnane, R. (2003) The skill content of recent technological change: An empirical exploration. Quarterly Journal of Economics 118(4), 1279-1333.

Autor, D.H., Katz, L.F. and Kearney, M.S. (2006) The Polarization of the U.S. Labor Market. American Economic Review 96(2), 189–94.

Autor, D.H., and Dorn, D. (2013) The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. American Economic Review, 103(5), 1553–97.

Autor, D.H., Katz, L.F., and Krueger, A.B. (1998) Computing inequality: have computers changed the labor market?. The Quarterly journal of economics, 113(4), 1169-1213.

Beaudry, P., and Green, D.A. (2005) Changes in U.S. wages, 1976– 2000: Ongoing skill bias or major technological change? Journal of Labor Economics 23(3), 1976–2000.

Beaudry, P., Green, D.A., and Sand, B. M. (2016) The great reversal in the demand for skill and cognitive tasks. Journal of Labor Economics, 34(S1), S199-S247.

Blau, F.D. and Kahn, L.M. (2006) The U.S. Gender Pay Gap in the 1990s: Slowing Convergence. Industrial & Labor Relations Review 60 (1), 45–66.

Börner, K., Scrivner, O., Gallant, M., Ma, S., Liu, X., Chewning, K., and Evans, J. A. (2018). Skill discrepancies between research, education, and jobs reveal the critical need to supply soft skills for the data economy. Proceedings of the National Academy of Sciences 115(50), 12630-12637.

Brynjolfsson, E. and McAfee, A. (2014) The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies, W. W. Norton & Company.

Caselli, F. (1999) Technological Revolutions. American Economic Review 89(May), 78-102.

Deming, D.J. (2017) The growing importance of social skills in the labor market. The Quarterly Journal of Economics, 132(4), 1593-1640.

Deming, D.J., and Kahn, L.B. (2018) Skill requirements across firms and labor markets: Evidence from job postings for professionals. Journal of Labor Economics, 36(S1), S337-S369.

Dorn, D. (2009) Essays on Inequality, Spatial Interaction, and the Demand for Skills. Dissertation University of St. Gallen no. 3613, September.

Goerlich, D. and Snower, D.J. (2013) Multitasking and Wages. CESifo Working Paper Series No. 4307.

Goldin, C. and Katz, L.F. (2010) The Race Between Education and Technology. Belknap Press.

Goos, M., A. Manning and A. Salomons (2014) Explaining job polarization: Routine-biased technological change and offshoring. American Economic Review 104(8): 2509-2526.

Goos, M., and A. Manning (2007) Lousy and Lovely Jobs: The Rising Polarization of Work in Britain. Review of Economics and Statistics, 89 (1), 118–33.

Graetz, G., and Michaels, G. (2018) Robots at work. Review of Economics and Statistics, 100(5), 753-768.

Guvenen, F., Kuruscu, B., Tanaka, S. and Wiczer, D. (2019) Multidimensional Skill Mismatch. American Economic Journal: Macroeconomics (forthcoming).

Hershbein, B., and Kahn, L.B. (2016) Do recessions accelerate routine-biased technological change? Evidence from vacancy postings (No. w22762) National Bureau of Economic Research.

Lemieux, T. (2008) The changing nature of wage inequality. Journal of Population Economics, Springer, 21(1): 21-48.

Leuven, E., Oosterbeek, H. and van Ophem, H. (2004) Explaining International Differences in Male Skill Wage Differentials by Differences in Demand and Supply of Skill The Economic Journal 114(495): 466-486

Lin, J. (2011) Technological Adaptation, Cities, and New Work. Review of Economics and Statistics, 93(2): 554–574.

Morgan, R.L., Hunt, E.S. and Carpenter, J.M. (1990) *Classification of Instructional Programs* (1990 ed.). Washington DC: U.S. Department of Education, National Center for Education Statistics.

Naticchioni, P., Ragusa, G. and Massari, R. (2014) Unconditional and Conditional Wage Polarization in Europe. IZA Discussion Paper No. 8465.

National Academy of Science, Committee on Occupational Classification and Analysis (1981) Fourth Edition Dictionary of DOT Scores for 1970 Census Categories. ICPSR Document No. 7845, Ann Arbor, MI.

Ross, M.B. (2017a) The Effect of Intensive Margin Changes to Task Content on Employment Dynamics over the Business Cycle. Mimeo.

Ross, M. B. (2017b) Routine-biased technical change: Panel evidence of task orientation and wage effects. Labour Economics, 48, 198-214.

Ruggles S, Flood S, Goeken R, Grover J, Meyer E, Pacas J, Sobek M (2018) IPUMS USA: Version 8.0 [dataset]. Minneapolis, MN: IPUMS, 2018.

Truthan, J.A. and Karman, S.E. (2003) Transferable Skills Analysis and Vocational Information During a Time of Transition. Journal of Forensic Vocational Analysis, 6(1), 17-25. (https://skilltran.com/pubs/TSATransition.htm)

Vona, F., and Consoli, D. (2015) Innovation and skill dynamics: a life-cycle approach. Industrial and Corporate Change, 24 (6), 1393-1415.

Weinberger, C.J. (2014) The increasing complementarity between cognitive and social skills. Review of Economics and Statistics, 96(4), 849–861.

Zeira, J. (1998) Workers, Machines, and Economic Growth. Quarterly Journal of Economics 113, 1091-111.

Appendix A – Validation of task measures

A1 DOT-O*NET match of tasks to build the measure of task variety

Table A1 – DOT-O*NET match of tasks to build the measure of task variety

Task category (ALM, 2003)	DOT description	DOT scale	O*NET description	O*NET scale
Non-routine analytical	REASON: Reasoning development	1-6	Critical thinking (skill, 2.A.2.a, level)	0-7 ↓ 1-6
	NUMERIC: Numerical aptitude	1-5	Processing information (work activity, 4.A.2.a.2, importance)	1-5
	SJC: Making judgments and decisions	0/1	Information ordering (ability, 1.A.1.b.6, importance, =1 if >=3, zero otherwise)	1-5
Non-routine interactive	DCP: Direction, control, planning	0/1	Judgment and decision making (skill, 2.B.4.e, importance, =1 if >=3, zero otherwise)	1-5
	DEPL: Dealing with people	0/1	Establishing and Maintaining Interpersonal Relationships (work activity, 4.A.4.a.4, importance, =1 if >=3, zero otherwise)	1-5
	VARCH: Variety and change	0/1	Organizing, Planning, and Prioritizing Work (work activity, 4.A.2.b.6, importance, =1 if >=3, zero otherwise)	1-5
Routine manual	FINGER: Finger dexterity	1-5	Finger dexterity (ability, 1.A.2.a.3, importance)	1-5
	STRENGTH: Strength	1-4	Average of Static strength (ability, 1.A.3.a.1, importance), Dynamic strength (ability, 1.A.3.a.3, importance) and Trunk strength (ability, 1.A.3.a.4, importance)	1-5
	FORM: Form Perception	1-5	Flexibility of closure (ability, 1.A.1.e.2, importance)	1-5
Routine cognitive	STS: Set limits, tolerances or standards	0/1	Operation and control (skill, 2.B.3.h, importance, =1 if >=3, zero otherwise)	1-5
	COLOR: Color discrimination	1-5	Visual color discrimination (ability, 1.A.4.a.3, importance)	1-5
	REPCON: Repetitive or continuous processes	0/1	Control precision (ability, 1.A.2.b.1, importance, =1 if >=3, zero otherwise)	1-5

Notes: Correspondence between all DOT task categories used in ALM (2003) with O*NET task categories.

To validate our measure, we introduce a measure of task variety that exploits the matching across 16 different task items between DOT and O*NET (see Data section in the main text). Our starting point is the recognition of the growing importance of task complexity (Acemoglu and Restrepo,

2017) and of multi-tasking (Goerlich and Snower, 2013; Weinberger, 2014; Borner et al., 2018) in response to technological change. Notably, Deming (2017) shows that when team production is important and a variety of jobs exist in the workplace, workers are able to exploit a comparative advantage via specialisation and the trading of tasks. In such a framework, workers with high cognitive skills possess higher productivity while workers with high social skills specialise and are able to trade tasks more efficiently thus improving their gains as well and leading to a degree of complementarity between the two. The authors further provide evidence on the wage gains from combining social and cognitive skills using data from the national longitudinal survey of youth.

To capture the relevance of changes in occupational task variety and multi-tasking we consider discrete changes in the importance of occupational tasks. As a first step, we build 16 dichotomous variables, one for each task (Table 1 and Table A1): the variable is coded 1 if the task intensity is larger than the central value of the theoretical distribution (i.e., larger than 3.5 for 1-6 scales, larger than 3 for 1-5 scales, larger than 0.5 for 0-1 scales). We then build two measures of task variety, one for routine tasks (routine manual and routine cognitive tasks) and one for non-routine tasks (non-routine analytical and non-routine interactive).

Descriptive evidence of the trends by macro-occupation in task variety measures is reported in Table A2. While the variety of routine tasks is on average low (below 1.5) and stable over time, the variety of non-routine tasks is much larger (3.89 on average) and increases substantially over time (+52%, on average, between 1980 and 2010). As expected, the variety in non-routine tasks is particularly important for Abstract occupations, while the variety of routine tasks is the largest in Service occupations. Non-routine task variety increases in all occupations, including Abstract occupations (for which the average value in 1980 was already very large, 5.87 compared to a theoretical maximum of 8). This evidence suggests that our measure of task variety is helpful in accounting for increases in the complexity of occupations that cannot be accounted for in the top occupations by our bounded measure of RTI.

Table A2 – Average task variety measures (weighted by hours worked multiplied by sample weights)

	All occupations	Abstract	Clerical	Manual	Services
	Task variety - Routine tasks				
1980	1.48	1.24	1.55	0.90	1.95
1990	1.45	1.31	1.33	0.97	1.95
2000	1.47	0.73	1.09	1.03	2.88
2010	1.39	0.89	0.67	0.70	2.96
Average	1.45	1.04	1.16	0.90	2.43
	Task variety - Non-routine tasks				
1980	3.28	5.87	3.06	1.92	1.22
1990	3.60	6.45	3.09	1.93	1.63
2000	3.71	6.57	3.68	1.83	1.38
2010	4.98	7.17	4.85	3.27	3.43
Average	3.89	6.51	3.67	2.24	1.92

Notes: Average task variety measures of occupations by macro occupational groups defined in Table A3. Weights used are the product of Census (1980; 1990; 2000) and ACS (2010) sampling weights and annual hours of labour supply

A2 Definition of macro-occupational groups

Table A3 – Definition of macro occupational groups (based on Dorn, 1999, and Acemoglu and Autor, 2011)

OCC1990	Occupation name
	Abstract occupations
4	Chief executives, public administrators, and legislators
7	Financial managers
8	Human resources and labor relations managers
13	Managers and specialists in marketing, advert., PR
14	Managers in education and related fields
15	Managers of medicine and health occupations
18	Managers of properties and real estate
22	Managers and administrators, n.e.c.
23	Accountants and auditors
24	Insurance underwriters
25	Other financial specialists
26	Management analysts
27	Personnel, HR, training, and labor rel. specialists
28	Purchasing agents and buyers of farm products
29	Buyers, wholesale and retail trade
33	Purchasing managers, agents, and buyers, n.e.c.
34	Business and promotion agents
36	Inspectors and compliance officers, outside
37	Management support occupations
43	Architects
44	Aerospace engineers
45	Metallurgical and materials engineers
47	Petroleum, mining, and geological engineers
48	Chemical engineers
53	Civil engineers
55	Electrical engineers
56	Industrial engineers

OCC1990	Occupation name
57	Mechanical engineers
59	Engineers and other professionals, n.e.c.
64	Computer systems analysts and computer scientists
65	Operations and systems researchers and analysts
66	Actuaries
68	Mathematicians and statisticians
69	Physicists and astronomists
73	Chemists
74	Atmospheric and space scientists
75	Geologists
76	Physical scientists, n.e.c.
77	Agricultural and food scientists
78	Biological scientists
79	Foresters and conservation scientists
83	Medical scientists
84	Physicians
85	Dentists
86	Veterinarians
87	Optometrists
88	Podiatrists
89	Other health and therapy occupations
95	Registered nurses
96	Pharmacists
97	Dieticians and nutritionists
98	Respiratory therapists
99	Occupational therapists
103	Physical therapists
104	Speech therapists
105	Therapists, n.e.c.
106	Physicians' assistants
154	Subject instructors, college
155	Kindergarten and earlier school teachers
156	Primary school teachers
157	Secondary school teachers
158	Special education teachers
159	Teachers, n.e.c.
164	Librarians
165	Archivists and curators
166	Economists, market and survey researchers
167	Psychologists
169	Social scientists and sociologists, n.e.c.
173	Urban and regional planners
178	Lawyers and judges
183	Writers and authors
184	Technical writers
185	Designers
186	Musicians and composers
187	Actors, directors, and producers
188	Painters, sculptors, craft-artists, and print-makers
189	Photographers
193	Dancers
194	Art/entertainment performers and related occs
195	Editors and reporters
198	Announcers
199	Athletes, sports instructors, and officials
203	Clinical laboratory technologies and technicians
204	Dental hygienists
205	Health record technologists and technicians
206	Radiologic technologists and technicians
207	Licensed practical nurses
208	Health technologists and technicians, n.e.c.
214	Engineering technicians

OCC1990	Occupation name
217	Drafters
218	Surveryors, cartographers, mapping scientists/techs
223	Biological technicians
224	Chemical technicians
225	Other science technicians
226	Airplane pilots and navigators
227	Air traffic controllers
228	Broadcast equipment operators
229	Computer software developers
234	Legal assistants and paralegals
473	Farmers (owners and tenants)
475	Farm managers
677	Optical goods workers
678	Dental laboratory and medical applicance technicians
	Blue-collar occupations
35	Construction inspectors
233	Programmers of numerically controlled machine tools
408	Laundry and dry cleaning workers
503	Supervisors of mechanics and repairers
505	Automobile mechanics and repairers
507	Bus, truck, and stationary engine mechanics
508	Aircraft mechanics
509	Small engine repairers
514	Auto body repairers
516	Heavy equipement and farm equipment mechanics
518	Industrial machinery repairers
519	Machinery maintenance occupations
523	Repairers of industrial electrical equipment
525	Repairers of data processing equipment
526	Repairers of household appliances and power tools
527	Telecom and line installers and repairers
533	Repairers of electrical equipment, n.e.c.
534	Heating, air conditioning, and refrigeration mechanics
535	Precision makers, repairers, and smiths
536	Locksmiths and safe repairers
539	Repairers of mechanical controls and valves
543	Elevator installers and repairers
544	Millwrights
549	Mechanics and repairers, n.e.c.
558	Supervisors of construction work
563	Masons, tilers, and carpet installers
567	Carpenters
573	Drywall installers
575	Electricians
577	Electric power installers and repairers
579	Painters, construction and maintenance
583	Paperhangers
584	Plasterers
585	Plumbers, pipe fitters, and steamfitters
588	Concrete and cement workers
589	Glaziers
593	Insulation workers
594	Paving, surfacing, and tamping equipment operators
595	Roofers and slaters
597	Structural metal workers
598	Drillers of earth
599	Misc. construction and related occupations
614	Drillers of oil wells
615	Explosives workers
616	Miners
617	Other mining occupations
628	Production supervisors or foremen

OCC1990	Occupation name
634	Tool and die makers and die setters
637	Machinists
643	Boilermakers
644	Precision grinders and fitters
645	Patternmakers and model makers
649	Engravers
657	Cabinetmakers and bench carpeters
658	Furniture/wood finishers, other prec. wood workers
666	Dressmakers, seamstresses, and tailors
668	Upholsterers
669	Shoemakers, other prec. apparel and fabric workers
675	Hand molders and shapers, except jewelers
679	Bookbinders
686	Butchers and meat cutters
687	Bakers
688	Batch food makers
694	Water and sewage treatment plant operators
695	Power plant operators
696	Plant and system operators, stationary engineers
699	Other plant and system operators
703	Lathe, milling, and turning machine operatives
706	Punching and stamping press operatives
707	Rollers, roll hands, and finishers of metal
708	Drilling and boring machine operators
709	Grinding, abrading, buffing, and polishing workers
713	Forge and hammer operators
719	Molders and casting machine operators
723	Metal platers
724	Heat treating equipment operators
727	Sawing machine operators and sawyers
729	Nail, tacking, shaping and joining mach ops (wood)
733	Other woodworking machine operators
734	Printing machine operators, n.e.c.
736	Typesetters and compositors
738	W inding and twisting textile and apparel operatives
739	Knitters, loopers, and toppers textile operatives
743	Textile cutting and dyeing machine operators
744	Textile sewing machine operators
745	Shoemaking machine operators
747	Clothing pressing machine operators
749	Miscellanious textile machine operators
753	Cementing and gluing machne operators
754	Packers, fillers, and wrappers
755	Extruding and forming machine operators
756	Mixing and blending machine operators
757	Separating, filtering, and clarifying machine operators
763	Food roasting and baking machine operators
764	Washing, cleaning, and pickling machine operators
765	Paper folding machine operators
766	Furnance, kiln, and oven operators, apart from food
769	Slicing, cutting, crushing and grinding machine
774	Photographic process workers
779	Machine operators, n.e.c.
783	Welders, solderers, and metal cutters
785	Assemblers of electrical equipment
799	Production checkers, graders, and sorters in
803	Supervisors of motor vehicle transportation
804	Truck, delivery, and tractor drivers
808	Bus drivers
809	Taxi cab drivers and chauffeurs
813	Parking lot attendants
823	Railroad conductors and yardmasters

OCC1990	Occupation name
824	Locomotive operators: engineers and firemen
825	Railroad brake, coupler, and switch operators
829	Ship crews and marine engineers
844	Operating engineers of construction equipment
848	Crane, derrick, winch, hoist, longshore operators
853	Excavating and loading machine operators
859	Stevedores and misc. material moving occupations
865	Helpers, constructions
866	Helpers, surveyors
869	Construction laborers
873	Production helpers
875	Garbage and recyclable material collectors
878	Machine feeders and offbearers
885	Garage and service station related occupations
887	Vehicle washers and equipment cleaners
888	Packers and packagers by hand
889	Laborers, freight, stock, and material handlers, n.e.c.
	Clerical occupations
243	Sales supervisors and proprietors
253	Insurance sales occupations
254	Real estate sales occupations
255	Financial service sales occupations
256	Advertising and related sales jobs
258	Sales engineers
275	Retail salespersons and sales clerks
276	Cashiers
277	Door-to-door sales, street sales, and news vendors
283	Sales demonstrators, promoters, and models
303	Office supervisors
308	Computer and peripheral equipment operators
313	Secretaries and stenographers
315	Typists
316	Interviewers, enumerators, and surveyors
317	Hotel clerks
318	Transportation ticket and reservation agents
319	Receptionists and other information clerks
326	Correspondence and order clerks
328	Human resources clerks, excl payroll and timekeeping
329	Library assistants
335	File clerks
336	Records clerks
337	Bookkeepers and accounting and auditing clerks
338	Payroll and timekeeping clerks
344	Billing clerks and related financial records processing
346	Mail and paper handlers
347	Office machine operators, n.e.c.
348	Telephone operators
349	Other telecom operators
354	Postal clerks, exluding mail carriers
355	Mail carriers for postal service
356	Mail clerks, outside of post office
357	Messengers
359	Dispatchers
364	Shipping and receiving clerks
365	Stock and inventory clerks
366	Meter readers
368	Weighers, measurers, and checkers
373	Material recording, sched., prod., plan., expediting cl.
375	Insurance adjusters, examiners, and investigators
376	Customer service reps, invest., adjusters, excl. insur.
377	Eligibility clerks for government prog., social welfare
378	Bill and account collectors

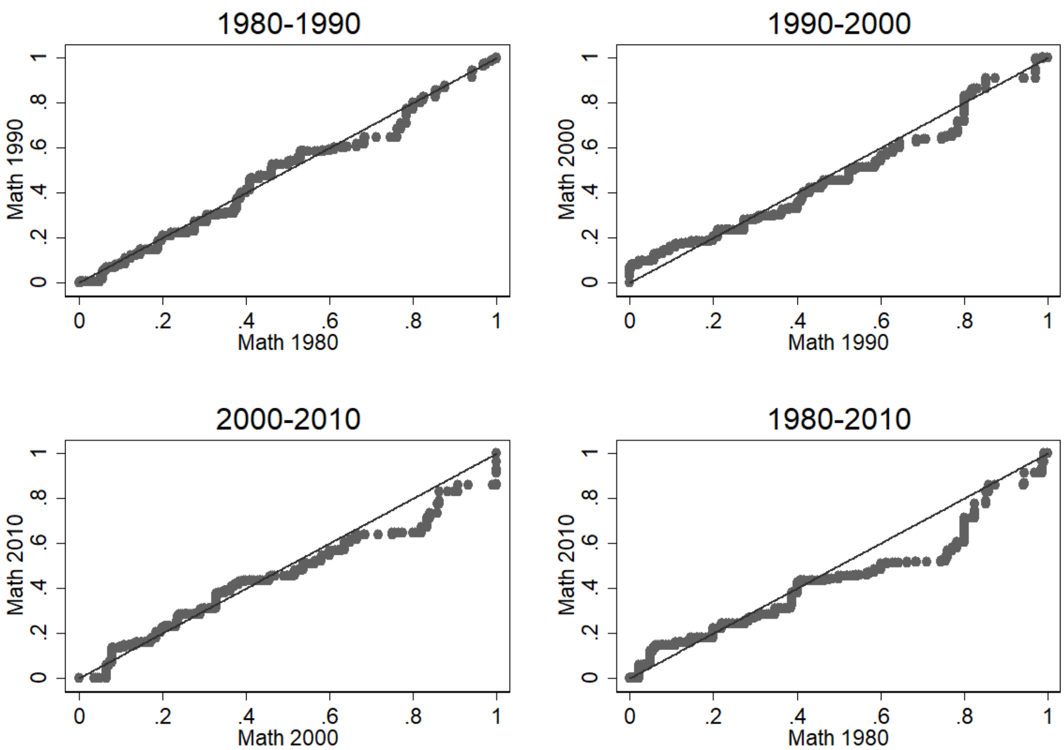
OCC1990	Occupation name
379	General office clerks
383	Bank tellers
384	Proofreaders
385	Data entry keyers
386	Statistical clerks
389	Administrative support jobs, n.e.c.
	Service occupations
19	Funeral directors
163	Vocational and educational counselors
174	Social workers
176	Clergy and religious workers
177	Welfare service workers
405	Housekeepers, maids, butlers, and cleaners
415	Supervisors of guards
417	Fire fighting, fire prevention, and fire inspection occs
418	Police and detectives, public service
423	Sheriffs, bailiffs, correctional institution officers
425	Crossing guards
426	Guards and police, except public service
427	Protective service, n.e.c.
434	Bartenders
435	Waiters and waitresses
436	Cooks
439	Food preparation workers
444	Miscellanious food preparation and service workers
445	Dental Assistants
447	Health and nursing aides
448	Supervisors of cleaning and building service
450	Superv. of landscaping, lawn service, groundskeeping
451	Gardeners and groundskeepers
453	Janitors
455	Pest control occupations
457	Barbers
458	Hairdressers and cosmetologists
459	Recreation facility attendants
461	Guides
462	Ushers
464	Baggage porters, bellhops and concierges
466	Recreation and fitness workers
467	Motion picture projectionists
468	Child care workers
469	Personal service occupations, n.e.c
470	Supervisors of personal service jobs, n.e.c
471	Public transportation attendants and inspectors
472	Animal caretakers, except farm
	Farm occupations
479	Farm workers, incl. nursery farming
488	Graders and sorters of agricultural products
489	Inspectors of agricultural products
496	Timber, logging, and forestry workers
498	Fishers, marine life cultivators, hunters, and kindred

A3 Quantile-to-quantile plots for selected tasks

The first validation of our matching procedure compares the distribution of task-related variables across different decades. We evaluate quantile-to-quantile plots which report the quantile of the variable in the left axis (in t+10 in our case) within the distribution of quantiles of the variable in the right axis (in t). When all dots lie on the diagonal, the rank distribution of the two variables is identical. A constant rank distribution does not necessarily mean a constant task across years. Results for all decades are reported in Figures A1, A2, A3, A4 and A5.

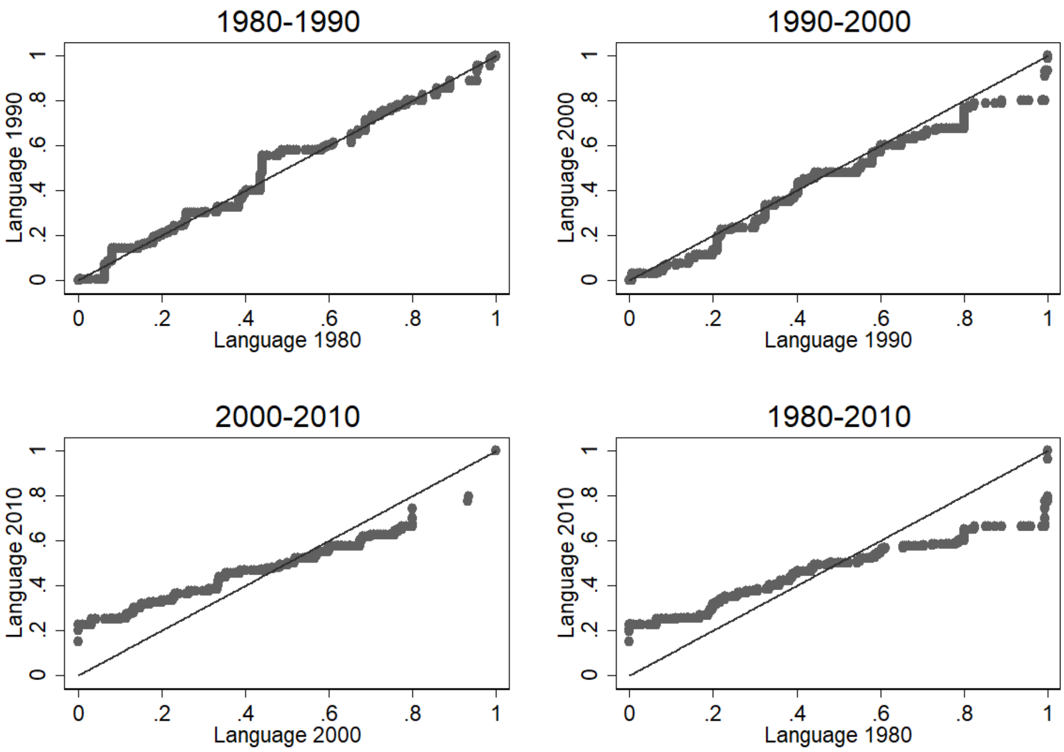
We do not observe any systematic differences in average tasks between years 1990 and 2000 (when O*NET was first introduced), nor in previous or subsequent periods (1980-1990 and 2000-2010). This is to say that, if systematic differences in the value of our task measures exist when matching DOT and O*NET, they are not necessarily due to our matching procedure. Even when some differences are apparent (e.g., Cleric and Manual in Figures A3 and A4), these differences cancel each other out when we aggregate information for the four task measures into our routinisation index (Figure A5).

Figure A1 – Quantile-to-quantile plot for MATH



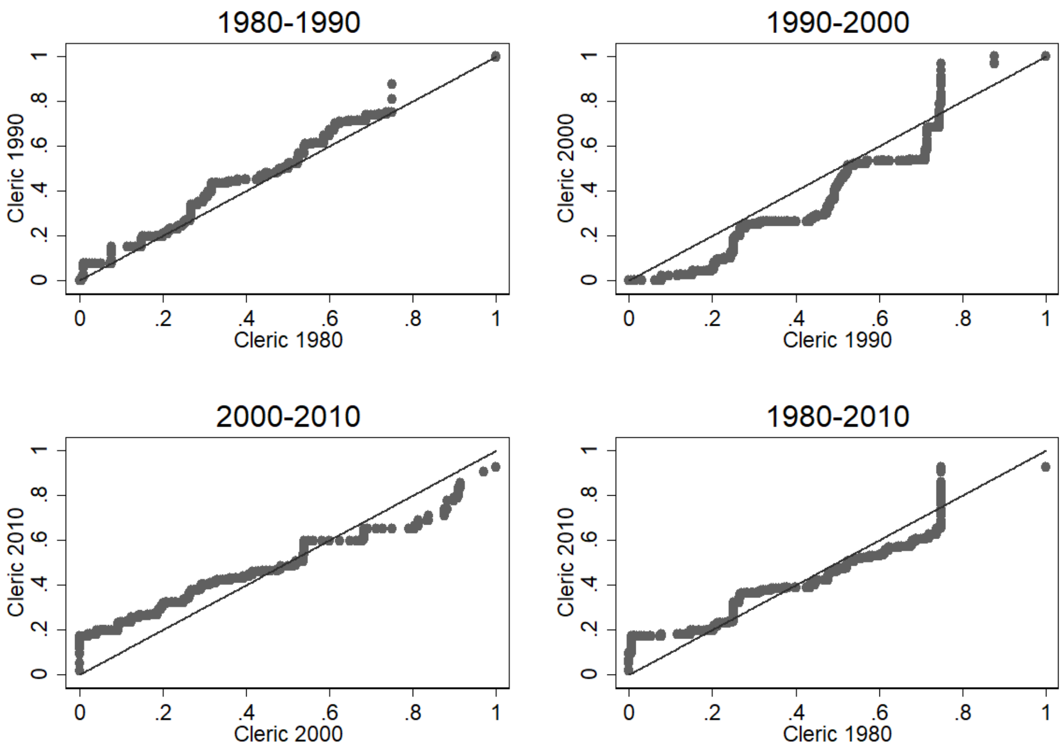
Notes: Quantiles weighted with the start of period product of Census (1980; 1990; 2000) sampling weights and annual hours of labour supply.

Figure A2 – Quantile-to-quantile plot for LANGUAGE



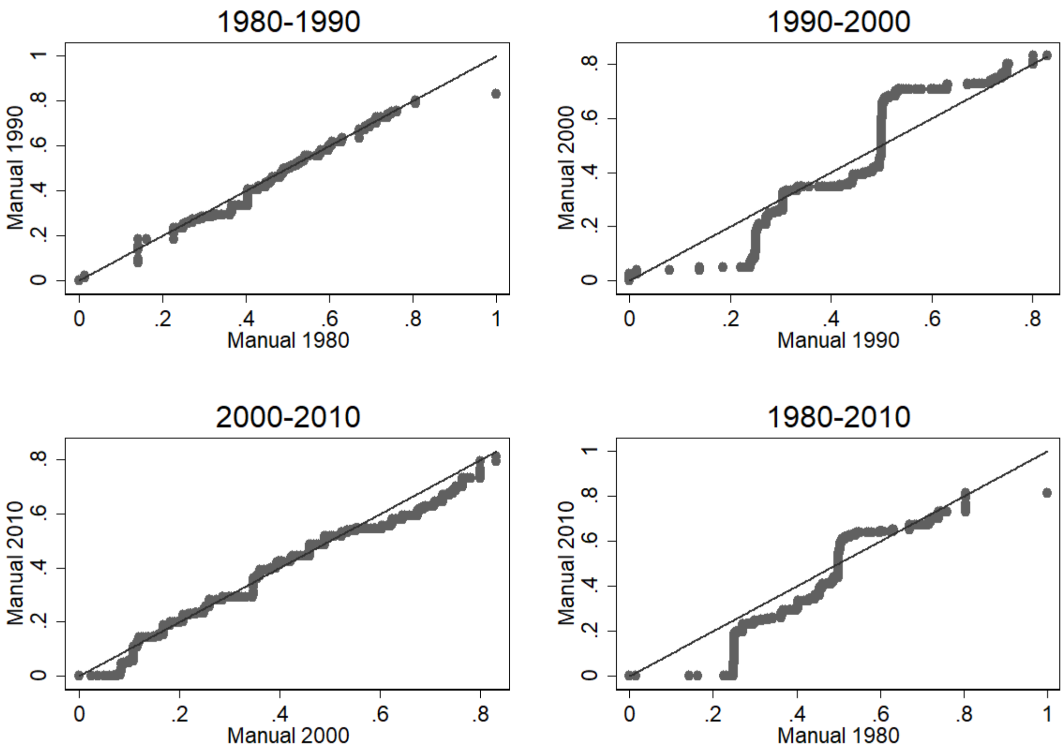
Notes: Quantiles weighted with the start of period product of Census (1980; 1990; 2000) sampling weights and annual hours of labour supply.

Figure A3 – Quantile-to-quantile plot for CLERIC



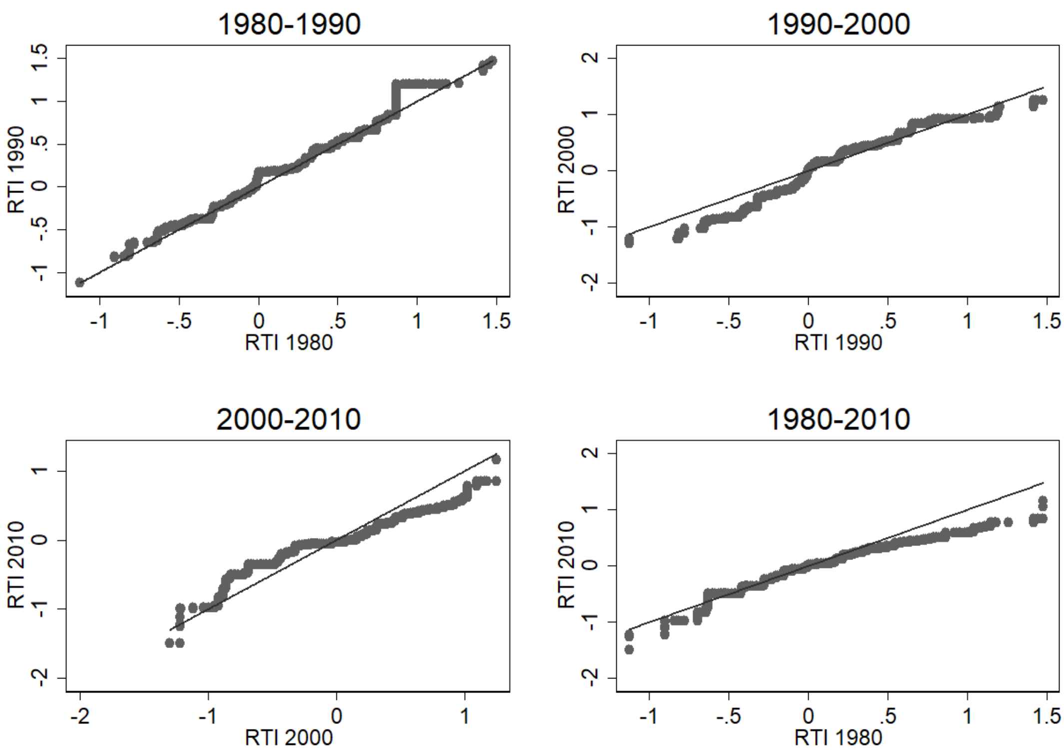
Notes: Quantiles weighted with the start of period product of Census (1980; 1990; 2000) sampling weights and annual hours of labour supply.

Figure A4 – Quantile-to-quantile plot for MANUAL



Notes: Quantiles weighted with the start of period product of Census (1980; 1990; 2000) sampling weights and annual hours of labour supply.

Figure A5 – Quantile-to-quantile plot for RTI



Notes: Quantiles weighted with the start of period product of Census (1980; 1990; 2000) sampling weights and annual hours of labour supply.

A4 Test of the difference in moments of tasks between decades

To validate our matching between task measures in DOT and O*NET we test for differences in the moments (from first to fourth) of the empirical distribution of tasks across occupations over different decades. We employ bootstrap tests (500 repetitions) for all moments. Results are reported in Table A4.

Table A4 – Bootstrap tests for the moments of DOT and O*NET distributions

1990-1980 (DOT91 - DOT77)					
	Math	Language	Cleric	Manual	RTI
Difference in average	0.014	0.025	0.036	0.036	-0.022
	(0.035)	(0.040)	(0.034)	(0.034)	(0.075)
Difference in standard deviation	0.008	0.008	-0.001	-0.001	0.017
	(0.017)	(0.019)	(0.020)	(0.020)	(0.046)
Difference in skewness	-0.157	-0.147	-0.172	-0.172	0.172
	(0.285)	(0.305)	(0.227)	(0.227)	(0.287)
Difference in kurtosis	-0.253	-0.170	0.0316	0.0316	0.0312
	(0.548)	(0.430)	(0.318)	(0.318)	(0.556)
2000-1990 (O*NET2000-DOT91)					
	Math	Language	Cleric	Manual	RTI
Difference in average	-0.010	-0.021	-0.070**	-0.024	-0.107
	(0.031)	(0.037)	(0.033)	(0.026)	(0.0838)
Difference in standard deviation	-0.029*	-0.012	0.045**	0.070***	0.114**
	(0.016)	(0.017)	(0.023)	(0.011)	(0.0448)
Difference in skewness	0.418	-0.203	0.637***	-0.089	-0.521*
	(0.305)	(0.287)	(0.212)	(0.256)	(0.272)
Difference in kurtosis	0.854	-0.149	0.713*	-0.744***	-0.883**
	(0.653)	(0.310)	(0.396)	(0.271)	(0.389)
2010-2000 (O*NET2010-O*NET2000)					
	Math	Language	Cleric	Manual	RTI
Difference in average	-0.008	0.049*	0.045	-0.021	-0.041
	(0.026)	(0.028)	(0.029)	(0.029)	(0.076)
Difference in standard deviation	-0.019	-0.096***	-0.079***	-0.010	-0.189***
	(0.016)	(0.013)	(0.027)	(0.013)	(0.035)
Difference in skewness	-0.257	0.143	0.067	-0.264	-0.132
	(0.349)	(0.305)	(0.254)	(0.245)	(0.279)
Difference in kurtosis	0.312	1.091	0.688	0.012	0.908*
	(0.896)	(0.690)	(0.567)	(0.234)	(0.540)

Notes: 500 repetitions on random bootstrap samples. Standard deviation of the test is reported in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Notes: Weights are the product of Census (1980; 1990; 2000) sampling weights and annual hours of labour supply.

First, we do not find any significant differences in the moments of the distributions of all tasks between 1980 and 1990 (i.e., within DOT). Second, we do observe some significant differences in the moments of the distributions between 1990 and 2000 for routine tasks (Cleric and Manual) and for the RTI, while no difference is found for non-routine tasks (Math and Language). These differences are, however, generally small in magnitude. Finally, significant differences (again relatively small) are also found between 2000 and 2010, i.e., within the O*NET era, suggesting that the 1990-2000 change may not be due primarily to the systematic differences between DOT and O*NET, which would have suggested that our match was not effective.

A5 Validation of task measures based on occupational computer use at work

Finally, as an additional robustness check we consider the relationship between on-the-job computer use of occupations (from different CPS Computer Use Supplement of October) and task measures (component-by-component and RTI). Results are reported in Table A5. All relationships are found to be strongly statistically significant and to have the expected sign: positively correlated with abstract tasks (MATH and LANGUAGE) and routine cognitive tasks (CLERIC), negative correlated with manual tasks (routine and non-routine manual tasks) and negatively correlated with the RTI. These strong correlations are consistent across different decades, suggesting that computer use is correlated with occupational task intensity with the expected sign both within DOT and within O*NET.

Table A5 – Validation of task measures: levels of tasks

	(1) Math	(2) Language	(3) Cleric	(4) Manual	(5) RTI	(6) NRM
Levels in 1990 (DOT)						
Computer use in 1989	0.611***	0.765***	0.665***	-0.276***	-1.176***	-0.295***
	(0.082)	(0.064)	(0.056)	(0.058)	(0.188)	(0.056)
R squared	0.403	0.503	0.552	0.216	0.369	0.234
Levels in 2000 (O*NET)						
Computer use in 1997	0.460***	0.581***	0.430***	-0.470***	-1.209***	-0.198***
	(0.051)	(0.055)	(0.084)	(0.050)	(0.175)	(0.048)
R squared	0.508	0.535	0.258	0.455	0.412	0.185
Levels in 2010 (O*NET)						
Computer use in 2003	0.377***	0.396***	0.425***	-0.525***	-0.910***	-0.321***
	(0.047)	(0.026)	(0.045)	(0.035)	(0.105)	(0.052)
R squared	0.415	0.707	0.532	0.621	0.532	0.354

Notes: N=322 occupations. OLS regression. weighted with employment weights. Robust standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Computer use measured as the share of workers in the occupation that use computers on the job (source: CPS Computer Use Supplement October 1989, 1997, 2003).

Appendix B – Additional descriptive analysis

Table B1 reports the three transition matrices (decade-by-decade) for our set of 322 occupations, split by decade. Overall, we observe a relatively large number of shifts of occupations across different quintiles of RTI. Shifts affect 18% of occupations in the first decade (1980-1990), 56% of occupations in the second decade (1990-2000) and 48% of the occupations in the third decade (2000-2010). Interestingly, a relatively small share of occupations shifts by two or more quintiles: none in 1980-1990, 42 (13% of occupations) in 1990-2000, 21 (6% of occupations) in 2000-2010. Finally, we observe just 4 shifts of three quintiles (3 in 1990-2000 and 1 in 2000-2010) and no shift of four quintiles.

Table B1 – Transition matrix of RTI

		Quintile of RTI 1990					
		1	2	3	4	5	Total
Quintile of RTI 1980	1	58	7	0	0	0	65
	2	11	50	3	0	0	64
	3	0	3	53	8	0	64
	4	0	0	8	47	9	64
	5	0	0	0	9	56	65
	Total	69	60	64	64	65	322

		Quintile of RTI 2000					
		1	2	3	4	5	Total
Quintile of RTI 1990	1	51	16	2	0	0	69
	2	13	28	15	2	2	60
	3	1	10	14	27	12	64
	4	0	9	20	16	19	64
	5	0	1	13	19	32	65
	Total	65	64	64	64	65	322

		Quintile of RTI 2010					
		1	2	3	4	5	Total
Quintile of RTI 2000	1	50	13	2	0	0	65
	2	15	31	15	2	1	64
	3	0	17	23	15	9	64
	4	0	3	20	24	17	64
	5	0	0	4	23	38	65
	Total	65	64	64	64	65	322

Notes: Number of occupations by (unweighted) quintile of RTI in *t* and *t-10*.

We present here the full decomposition of the within and between components, using the following formula:

$$\Delta RTI = \sum_{i,o}\left[\overline{\delta_\iota\phi_{\iota,o}}\Delta RTI_o + \overline{\delta_\iota}\Delta\phi_{i,o}RTI_o^{1980} + \Delta\delta_i\overline{\phi_{\iota o}}RTI_o^{1980} + \overline{\delta_\iota}\Delta\phi_{i,o}(\overline{RTI_o} - RTI_o^{1980}) + \Delta\delta_i\overline{\phi_{\iota o}}(\overline{RTI_o} - RTI_o^{1980})\right] \quad \text{(B.1)}$$

where $\overline{\delta_\iota}\Delta\phi_{i,o}RTI_o^{1980}$ and $\Delta\delta_i\overline{\phi_{\iota o}}RTI_o^{1980}$ are, respectively, the 'pure' between occupation and between industry components (calculated with the initial RTI). On the other hand, $\overline{\delta_\iota}\Delta\phi_{i,o}(\overline{RTI_o} - RTI_o^{1980})$ and $\Delta\delta_i\overline{\phi_{\iota o}}(\overline{RTI_o} - RTI_o^{1980})$ represent the covariance components of, respectively, the between-occupation and between-industry components. As is evident from Table B2, the two covariance terms $\overline{\delta_\iota}\Delta\phi_{i,o}(\overline{RTI_o} - RTI_o^{1980})$ and $\Delta\delta_i\overline{\phi_{\iota o}}(\overline{RTI_o} - RTI_o^{1980})$ appear relatively small compared to the other terms, so we focus on the simpler decomposition. Tables B3 and B4 replicate the full decomposition by macro-occupational and industry groups, respectively.

Table B2– Full decomposition of RTI

	1980-1990	1990-2000	2000-2010	1980-2010
Within occupation	**0.022**	**-0.072**	**-0.011**	**-0.062**
Between occupation (with RTI_o^{1980})	*-0.032*	*-0.022*	*-0.002*	*-0.057*
Covariance between occupation	*0.001*	*-0.003*	*-0.008*	*-0.010*
Total between occupation	**-0.032**	**-0.025**	**-0.011**	**-0.067**
Between industry (with RTI_o^{1980})	*-0.020*	*-0.011*	*-0.013*	*-0.044*
Covariance between industry	*0.001*	*0.001*	*0.004*	*0.006*
Total between industry	**-0.018**	**-0.010**	**-0.009**	**-0.037**
Total change	**-0.028**	**-0.107**	**-0.031**	**-0.166**

Notes: Decomposition of RTI based on equations 2 (bold) and B.1 (italics). Weights are the product of Census (1980; 1990; 2000) sampling weights and annual hours of labour supply.

Table B3– Full decomposition of RTI by decade and occupation

	1980-1990	1990-2000	2000-2010	1980-2010
	Abstract			
Within occupation	**0.026**	**-0.175**	**0.140**	**-0.009**
Between occupation (with RTI_o^{1980})	*-0.002*	*-0.017*	*0.002*	*-0.017*
Covariance between occupation	*-0.001*	*0.013*	*-0.006*	*0.007*
Total between occupation	**-0.002**	**-0.004**	**-0.003**	**-0.010**
Between industry (with RTI_o^{1980})	*-0.003*	*0.002*	*0.006*	*0.004*
Covariance between industry	*0.001*	*0.002*	*0.003*	*0.006*
Total between industry	**-0.002**	**0.003**	**0.009**	**0.010**
Total change	**0.022**	**-0.176**	**0.145**	**-0.009**
	Clerical			
Within occupation	**0.012**	**-0.050**	**-0.0750**	**-0.113**
Between occupation (with RTI_o^{1980})	*-0.028*	*-0.021*	*-0.002*	*-0.051*
Covariance between occupation	*-0.003*	*-0.010*	*-0.005*	*-0.017*
Total between occupation	**-0.031**	**-0.031**	**-0.007**	**-0.068**
Between industry (with RTI_o^{1980})	*-0.008*	*-0.003*	*0.002*	*-0.008*
Covariance between industry	*0.001*	*0.002*	*-0.003*	*0.000*
Total between industry	**-0.007**	**-0.001**	**-0.001**	**-0.008**
Total change	**-0.026**	**-0.082**	**-0.082**	**-0.190**
	Blue collar			
Within occupation	**0.010**	**0.026**	**-0.170**	**-0.134**
Between occupation (with RTI_o^{1980})	*0.002*	*-0.003*	*0.026*	*0.025*
Covariance between occupation	*0.003*	*-0.008*	*-0.013*	*-0.018*
Total between occupation	**0.004**	**-0.011**	**0.013**	**0.006**
Between industry (with RTI_o^{1980})	*-0.003*	*-0.008*	*-0.004*	*-0.015*
Covariance between industry	*0.001*	*-0.001*	*0.002*	*0.003*
Total between industry	**-0.002**	**-0.009**	**-0.001**	**-0.011**
Total change	**0.013**	**0.006**	**-0.158**	**-0.139**
	Service			
Within occupation	**0.068**	**-0.081**	**0.018**	**0.004**
Between occupation (with RTI_o^{1980})	*-0.010*	*-0.021*	*0.015*	*-0.016*
Covariance between occupation	*0.001*	*-0.002*	*-0.006*	*-0.007*
Total between occupation	**-0.009**	**-0.023**	**0.009**	**-0.023**
Between industry (with RTI_o^{1980})	*-0.006*	*-0.010*	*-0.004*	*-0.021*
Covariance between industry	*0.002*	*-0.004*	*0.003*	*0.001*
Total between industry	**-0.005**	**-0.014**	**-0.001**	**-0.020**
Total change	**0.054**	**-0.118**	**0.026**	**-0.038**

Notes: Decomposition of RTI based on equations 2 (bold) and B.1 (italics). Macro-occupational groups defined in Table A3. Weights are the product of Census (1980; 1990; 2000) sampling weights and annual hours of labour supply.

Table B4 – Full decomposition of RTI by decade and industry

	1980-1990	1990-2000	2000-2010	1980-2010
	Manufacturing industries			
Within occupation	**0.004**	**-0.054**	**-0.088**	**-0.138**
Between occupation (with RTI_o^{1980})	*-0.026*	*-0.022*	*0.002*	*-0.046*
Covariance between occupation	*-0.021*	*-0.010*	*-0.033*	*-0.064*
Total between occupation	**-0.048**	**-0.032**	**-0.031**	**-0.110**
Between industry (with RTI_o^{1980})	*-0.009*	*-0.008*	*-0.006*	*-0.023*
Covariance between industry	*-0.003*	*0.011*	*-0.006*	*0.002*
Total between industry	**-0.012**	**0.002**	**-0.012**	**-0.021**
Total change	**-0.055**	**-0.083**	**-0.131**	**-0.270**
	Non-manufacturing industries			
Within occupation	**0.027**	**-0.076**	**0.003**	**-0.046**
Between occupation (with RTI_o^{1980})	*-0.051*	*-0.022*	*-0.028*	*-0.102*
Covariance between occupation	*0.024*	*-0.001*	*0.021*	*0.045*
Total between occupation	**-0.027**	**-0.023**	**-0.007**	**-0.057**
Between industry (with RTI_o^{1980})	*-0.013*	*0.003*	*-0.010*	*-0.019*
Covariance between industry	*0.004*	*-0.011*	*0.007*	*0.000*
Total between industry	**-0.009**	**-0.008**	**-0.003**	**-0.020**
Total change	**-0.008**	**-0.107**	**-0.007**	**-0.123**

Notes: Decomposition of RTI based on equations 2 (bold) and B.1 (italics). Macro-occupational groups defined in Table A3. Weights are the product of Census (1980; 1990; 2000) sampling weights and annual hours of labour supply.

Appendix C – RTI and education

To measure average educational attainment of occupations we use data from the decennial census (1980, 1990, 2000) and ACS (2010) to identify three groups: 'High School' is the share (weighted by hours worked times sample weights) of workers that completed Grade 12 or GED-equivalent (General Educational Development); 'College' is the weighted share of workers that completed a college degree; 'Post-Graduate' is the weighted share of workers with educational attainment beyond the completion of the college degree.

To analyse instructional programmes, we rely on a standard taxonomy provided by the National Center for Education Statistics (NCES): the Classification of Instructional Programs (CIP; Morgan et al., 1990) which lists educational programmes, provides subject matter names as well as short descriptions (apart from the 1985 edition for which only a general title is available) at different levels of aggregation. Most CIP titles refer to academic and occupational instructional programmes at the postsecondary level. We employ CIP at the most detailed level of disaggregation (6-digits) for the different editions available: 1985 (463 unique programmes), 1990 (1458 unique programmes), 2000 (1432 unique programmes) and 2010 (1720 unique programmes). Following the guidelines provided by the NCES[25], we group the different instructional programmes in business- and technical-related programmes. The classification was also manually checked by the authors and several programmes were reallocated to the correct group (business or technical). We then merge different CIP editions using the crosswalks provided by the NCES, obtaining a correspondence between the different CIP editions under CIP2010 6-digit codes. Finally, the NCES and BLS provide a crosswalk mapping of the 1516 CIP2010 6-digit codes into 623 SOC2010 6-digit occupation codes, where the instructional programmes serve as preparation for each occupation.[26] Table C1 reports the total number of instructional programmes and the number of business- and technical-related programmes aggregated at the 2-digit SOC2010 code for the overall period (1985-2010).

[25] For a description of how NCES distinguishes between academic/general programmes and vocational training programmes, see: https://nces.ed.gov/ipeds/cipcode/Files/Introduction_CIP2010.pdf. Business-related instructional programmes are programs which help to develop skills for managerial roles within public and private organisations. Technical-related programmes mainly refer to STEM disciplines.

[26] The crosswalk is unable to match 204 unique CIP2010 codes.

Table C1 – Description of instructional programmes

SOC2010 2-digit	SOC2010 2-digit title	Number of programmes	Number of business programmes	Number of technical programmes
11	Management Occupations	1346	446	160
13	Business and Financial Operations Occupations	281	221	33
15	Computer and Mathematical Occupations	358	4	343
17	Architecture and Engineering Occupations	379	3	132
19	Life, Physical, and Social Science Occupations	1030	105	67
21	Community and Social Service Occupations	206	26	2
23	Legal Occupations	62	62	0
25	Education, Training, and Library Occupations	3069	372	252
27	Arts, Design, Entertainment, Sports, and Media Occupations	792	243	89
29	Healthcare Practitioners and Technical Occupations	841	11	11
31	Healthcare Support Occupations	70	8	8
33	Protective Service Occupations	129	17	6
35	Food Preparation and Serving Related Occupations	75	25	0
37	Building and Grounds Cleaning and Maintenance Occupations	31	16	0
39	Personal Care and Service Occupations	105	15	2
41	Sales and Related Occupations	148	117	3
43	Office and Administrative Support Occupations	142	75	59
45	Farming, Fishing, and Forestry Occupations	83	12	0
47	Construction and Extraction Occupations	153	2	0
49	Installation, Maintenance, and Repair Occupations	201	7	24
51	Production Occupations	257	23	31
53	Transportation and Material Moving Occupations	70	0	0
55	Military Specific Occupations	54	13	23

The CIP number is aggregated within each IND1990 occupation as the simple average (uniform weights) of CIP for each occupational title.

To estimate the change in education-related features predicted by changes in the task content of occupations, we follow Spitz-Oener (2006). Estimated predicted changes, reported in Table 7, are based on the econometric estimates (equation 5) reported in Table C2. Overall, we observe that routine-intensive occupations are more common among high-school graduates (column 1), with a relationship that appears to be growing with time. The share of college and post-graduate degree recipients within an occupation is negatively related to its average routine intensity, even though this link appears to be shrinking over time. Finally, routine-intensive occupations have a lower number of instructional programmes, and even more so in more recent decades.

Considering the R squared of the regressions, we observe a good explanatory power of RTI for educational attainment (around 50% for high-school and college, lower for post-graduate) and the number of instructional programmes (23.6%), while the predicting power is poor for the share of 'business' instructional programmes and, even more so, for the share of technical instructional programmes.

Table C2 – Results for education

	(1)	(2)	(3)	(4)	(5)	(6)
	High school	College	Post-graduate	Number of instructional programmes	Share of 'business' instructional programmes	Share of 'technical' instructional programmes
RTI	0.185***	-0.468***	-0.228***	-4.513**	-0.365***	-0.065
	(0.027)	(0.042)	(0.036)	(2.234)	(0.070)	(0.050)
RTI x D1990	0.057***	0.025	0.042***	-3.375***	0.008	-0.003
	(0.013)	(0.020)	(0.010)	(1.005)	(0.039)	(0.014)
RTI x D2000	0.031	0.124***	0.083***	-3.380**	0.101*	0.024
	(0.025)	(0.035)	(0.019)	(1.525)	(0.055)	(0.031)
RTI x D2010	0.169***	-0.098**	-0.030	-12.203**	-0.049	-0.026
	(0.031)	(0.043)	(0.024)	(5.900)	(0.069)	(0.031)
D1990	-0.046***	-0.020***	-0.019***	2.214***	0.018	-0.004
	(0.007)	(0.006)	(0.004)	(0.519)	(0.021)	(0.007)
D2000	0.040***	-0.041***	-0.028***	2.832***	-0.024	0.012
	(0.011)	(0.013)	(0.007)	(0.742)	(0.023)	(0.011)
D2010	0.015	-0.009	-0.021***	4.159***	-0.034	0.011
	(0.011)	(0.012)	(0.006)	(1.250)	(0.026)	(0.012)
Constant	0.340***	0.350***	0.126***	3.074***	0.332***	0.092***
	(0.014)	(0.022)	(0.018)	(0.904)	(0.048)	(0.025)
Joint significance of RTI (F test)	46.053***	123.616***	40.763***	4.081**	27.010***	1.714
R squared	0.452	0.534	0.266	0.236	0.152	0.0150
N	1267	1267	1267	1210	1278	1278

Notes: OLS model. Weights are the product of Census (1980; 1990; 2000) sampling weights and annual hours of labour supply. Robust standard errors clustered at occupation level are in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

Appendix D – Robustness checks

We here report three robustness checks for our estimate of the link between RTI and occupational employment (equation 5). In Table D1 we calculated average task importance and level within occupation by using employment weights for detailed occupations from the CPS 1971 Monthly File. In this way, we do not account for the emergence of 'new jobs' (i.e., new occupational titles not available in 1971). Results appear to be in line with our baseline results (Table 8) in terms of sign, magnitude and statistical significance.

Table D1 – Robustness check: average occupational tasks weighted using CPS 1971 Monthly File occupational weights

Panel A - Only initial RTI					
Dep: Δlog(Empl)	1980-1990	1990-2000	2000-2010	1980-2010	1980-2010 stacked
Initial RTI	-0.232***	-0.138**	-0.079**	-0.493***	-0.130***
	(0.051)	(0.061)	(0.039)	(0.117)	(0.028)
Offshorability	0.423	-0.402	-0.120	0.176	0.450
	(0.395)	(0.391)	(0.203)	(0.697)	(0.335)
Initial man task	0.201	0.082	0.050	0.438	0.111
	(0.191)	(0.266)	(0.098)	(0.401)	(0.118)
R sq	0.312	0.179	0.380	0.364	0.260
N	29847	28897	28083	26531	86827
Panel B - Initial and change of RTI					
Dep: Δlog(Empl)	1980-1990	1990-2000	2000-2010	1980-2010	1980-2010 stacked
Initial RTI	-0.226***	-0.113*	-0.075	-0.689***	-0.165***
	(0.056)	(0.060)	(0.053)	(0.119)	(0.038)
ΔRTI	0.225	-0.253***	0.009	-0.509**	-0.148***
	(0.266)	(0.088)	(0.082)	(0.205)	(0.056)
Offshorability	0.463	-0.472	-0.114	-0.151	0.393
	(0.413)	(0.380)	(0.217)	(0.739)	(0.337)
Initial man task	0.200	0.087	0.0501	0.498	0.105
	(0.190)	(0.258)	(0.099)	(0.382)	(0.119)
R sq	0.314	0.188	0.380	0.370	0.264
N	29847	28897	28083	26531	86827

Notes: OLS model. All models include industry dummies. Weights are the product of Census (1980; 1990; 2000) sampling weights and annual hours of labour supply. Robust standard errors clustered at occupation level are in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. In the stacked differences specification offshorability (unreported) and industry dummies are interacted with period dummies. Occupational titles within each *OCC1990* occupation are based on occupational employment estimates from the CPS 1971 Monthly File.

As a second robustness check, we repeat our analysis by using a modified version of the RTI index which also accounts for the importance of non-routine manual tasks. This index, labelled as RTI^{NRM}, is computed as follows:

$$RTI_{o,t}^{NRM} = \log\left(\frac{CLERIC_{o,t}+MANUAL_{o,t}}{\frac{1}{2}MATH_{o,t}+\frac{1}{2}LANG_{o,t}+EYEHAND_{o,t}}\right) \tag{D.1}$$

Results are reported in Table D2. In general, while the results appear to be in line with our baseline results (Table 8) in terms of sign and statistical significance, we observe that employment change appears to be more strongly correlated with the initial level of RTI compared to our baseline results. This difference, however, is generally small.

Table D2 – Robustness check: RTI computed including non-routine manual task intensity (RTI^{NRM})

Panel A - Only initial RTI^{NRM}					
	(1)	(2)	(3)	(4)	(5)
Dep: Δlog(Empl)	1980-1990	1990-2000	2000-2010	1980-2010	1980-2010 stacked
Initial RTI^{NRM}	-0.298***	-0.179**	-0.106**	-0.665***	-0.168***
	(0.080)	(0.088)	(0.043)	(0.149)	(0.040)
Offshorability	0.670**	-0.391	0.062	0.613	0.713**
	(0.280)	(0.350)	(0.188)	(0.525)	(0.280)
R sq	0.319	0.179	0.382	0.370	0.262
N	29847	28897	28083	26531	86827
Panel B - Initial and change of RTI^{NRM}					
	(1)	(2)	(3)	(4)	(5)
Dep: Δlog(Empl)	1980-1990	1990-2000	2000-2010	1980-2010	1980-2010 stacked
Initial RTI^{NRM}	-0.275***	-0.150*	-0.083*	-0.796***	-0.210***
	(0.097)	(0.083)	(0.049)	(0.155)	(0.052)
ΔRTI^{NRM}	0.291	-0.307**	0.048	-0.322*	-0.172**
	(0.348)	(0.129)	(0.069)	(0.189)	(0.083)
Offshorability	0.714**	-0.544	0.065	0.524	0.678**
	(0.283)	(0.360)	(0.184)	(0.550)	(0.278)
R sq	0.321	0.188	0.382	0.372	0.265
N	29847	28897	28083	26531	86827

Notes: OLS model. All models include industry dummies. Weights are the product of Census (1980; 1990; 2000) sampling weights and annual hours of labour supply. Robust standard errors clustered at occupation level are in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. In the stacked differences specification offshorability (unreported) and industry dummies are interacted with period dummies. RTI^{NRM} is defined as in equation D.1.

Finally, we also repeat our analysis for a less demanding specification in which we exclude from the specification all occupation-specific control variables except RTI (i.e., Offshorability and Initial manual task intensity). Results are shown in Table D3. Again, baseline results (Table 8) are generally confirmed, with the only exception being a not significant link between initial RTI and employment change in Panel B for the decade 1990-2000.

Table D3 – Robustness check: results without additional occupation-level control variables

Panel A - Only initial RTI					
Dep: Δlog(Empl)	1980-1990	1990-2000	2000-2010	1980-2010	1980-2010 stacked
Initial RTI	-0.236***	-0.116**	-0.075**	-0.473***	-0.120***
	(0.049)	(0.054)	(0.030)	(0.110)	(0.025)
R sq	0.310	0.177	0.380	0.363	0.258
N	30015	29088	28083	26693	87186

Panel B - Initial and change of RTI					
Dep: Δlog(Empl)	1980-1990	1990-2000	2000-2010	1980-2010	1980-2010 stacked
Initial RTI	-0.232***	-0.088	-0.058	-0.598***	-0.143***
	(0.052)	(0.060)	(0.042)	(0.121)	(0.036)
ΔRTI	0.191	-0.213**	0.040	-0.402**	-0.124*
	(0.248)	(0.106)	(0.082)	(0.194)	(0.069)
R sq	0.311	0.183	0.380	0.366	0.261
N	30015	28897	28083	26531	86995

Notes: OLS model. All models include industry dummies. Weights are the product of Census (1980; 1990; 2000) sampling weights and annual hours of labour supply. Robust standard errors clustered at occupation level are in parenthesis. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

ABOUT OFCE

The Paris-based Observatoire français des conjonctures économiques (OFCE), or French Economic Observatory is an independent and publicly-funded centre whose activities focus on economic research, forecasting and the evaluation of public policy.

Its 1981 founding charter established it as part of the French Fondation nationale des sciences politiques (Sciences Po), and gave it the mission is to "ensure that the fruits of scientific rigour and academic independence serve the public debate about the economy". The OFCE fulfils this mission by conducting theoretical and empirical studies, taking part in international scientific networks, and assuring a regular presence in the media through close cooperation with the French and European public authorities. The work of the OFCE covers most fields of economic analysis, from macroeconomics, growth, social welfare programmes, taxation and employment policy to sustainable development, competition, innovation and regulatory affairs.

ABOUT SCIENCES PO

Sciences Po is an institution of higher education and research in the humanities and social sciences. Its work in law, economics, history, political science and sociology is pursued through ten research units and several crosscutting programmes.

Its research community includes over two hundred twenty members and three hundred fifty PhD candidates. Recognized internationally, their work covers a wide range of topics including education, democracies, urban development, globalization and public health.
One of Sciences Po's key objectives is to make a significant contribution to methodological, epistemological and theoretical advances in the humanities and social sciences. Sciences Po's mission is also to share the results of its research with the international research community, students, and more broadly, society as a whole.

PARTNERSHIP