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# Measuring Routine and Cognitive Task Indices Using Large Language Models to Analyze Occupational Change in the United States<sup>\*,\*\*</sup>

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## Abstract

This study proposes an innovative methodology for quantifying Routine Task Intensity (RTI) and Cognitive Task Intensity (CTI) using Large Language Models to analyze O\*NET task descriptions. Employing these LLM-derived measures, we reveal a consistent decline in routine occupations across service and sales sectors, with sales receiving limited attention in existing literature. Regression analysis indicates a significant upward trend in cognitive impact on wages for females, particularly in service, sales, and to a lesser extent, management occupations, while routine coefficients remain stable across five decades. These results underscore the growing significance of cognitive skills, especially for women in the workforce. Despite limitations in LLM output reliability and replicability, our methodology offers a complementary perspective to existing approaches, enabling a comprehensive understanding of labor market transformations.

JEL Codes: J21, J24, J62, O33

**Keywords:** Routine Task Intensity Cognitive Task Intensity Large Language Models Job Polarization Occupational Change

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\*Replication data and code (open main.do after download): <https://tinyurl.com/32s94jjw>

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## 1. Introduction

Numerous empirical investigations have elucidated the phenomenon of middle-skill employment attrition through the lens of Routine-Biased Technological Change (RBTC) (Autor et al., 2006; Goos et al., 2014, 2009). However, this theoretical framework is not without contention (Fernández-Macías and Hurley, 2017). Central to this discourse is the operationalization and quantification of Routine Task Intensity (RTI). The methodological approach to RTI measurement significantly influences the outcomes of labor market polarization analyses (Walo, 2023).

Walo (2023) identifies approximately six distinct methodologies for RTI quantification extant in the literature. The most widely adopted approach, pioneered by Autor et al. (2003), utilizes the 1977 Dictionary of Occupational Titles (DOT). Alternative methodologies incorporate data from O\*NET, BERUFENET, or the Programme for the International Assessment of Adult Competencies (PIAAC). While Walo (2023) provides a comprehensive comparative analysis of these approaches, the author concludes that “all RTI measures have conceptual strengths and weaknesses, ... , and that some measures are better predictors of occupational change than others.” This underscores the necessity for careful consideration in selecting appropriate RTI metrics for labor market analyses.

This study proposes a novel, seventh method for measuring RTI by leveraging O\*NET (National Center for ONET Development, 2023) task descriptions. This innovative approach represents the first application of Large Language Models (LLMs) in the RTI measurement literature. Additionally, following the work of Cortes et al. (2017) and Fernández-Macías and Hurley (2017), we introduce a Cognitive Task Intensity (CTI) using similar LLM-based techniques. In line with numerous extant studies, such as Cortes et al. (2020), we adopt a two-dimensional framework: Routine versus Non-routine, and Cognitive versus Manual (Non-cognitive). This bifurcation results in a four-category classification system. To distinguish our methodology from traditional RTI and CTI measurements, we introduce the term RTI-LLM (RTI measured by LLMs), and CTI-LLM (CTI measured by LLMs).

Existing RTI measurement methods have faced various limitations (Walo, 2023). Autor and Dorn (2013) approach uses only three variables from DOT, while Autor et al. (2003) employ five. These RTI measures are widely adopted in the literature, suggesting their general acceptance among researchers. However, some scholars have raised concerns. One critique posits that these methods may not fully capture the concept of ‘repetitiveness,’ which is fundamental to routine tasks. Haslberger (2022) notes, these approaches “completely fail to capture key

aspects of the notion of routine ... most importantly, repetitiveness.” Moreover, [Fernández-Macías and Hurley \(2017\)](#) states that “The previously mentioned paper of [Autor et al. \(2003\)](#) ... the component of repetitiveness is not even considered and the use of finger dexterity as an indicator of routine seems difficult to justify.”

The use of DOT, while suitable for studying labor economics from the 1970s to the 1990s, has become less appropriate for contemporary analyses. To address this limitation, some researchers have adopted the more current O\*NET database ([Freeman et al., 2020](#)). However, approaches such as that of [Goos et al. \(2009\)](#), which incorporate 96 variables selected from the 162 provided by O\*NET, present certain methodological challenges. These challenges include determining which factors are most relevant to routineness and how they should be appropriately weighted.

Meanwhile, two additional methodologies for measuring RTI have been developed: one by [Fernández-Macías and Hurley \(2017\)](#), introducing a novel task categorization approach, and another by [Marcolin et al. \(2016\)](#), utilizing PIAAC surveys. These methods, which employ similar procedures, significantly contribute to task measurement and analysis. [Walo \(2023\)](#) provides a comprehensive explanation and comparative analysis of these measurement processes.

We propose a novel method, termed RTI-LLM, initiates with a comprehensive compilation of task descriptions for each occupation, systematically categorized in accordance with the six-digit Standard Occupational Classification (SOC) system. Utilizing the natural language understanding capabilities of LLMs, we assess each task description for its degree of routineness. The LLM assigns a value on a continuous scale from 0 (Non-routine) to 1 (Routine) for each task. These individual task scores are then averaged within each six-digit SOC occupational category to derive the RTI-LLM scores for that occupation.

A parallel process is employed to measure cognitiveness. The LLM evaluates each task description on a scale from 0 (Manual, i.e. Non-cognitive) to 1 (Cognitive). These task-level cognitive scores are similarly averaged within each six-digit SOC occupational category. This methodology harnesses the semantic understanding capabilities of LLMs to provide a nuanced evaluation of task characteristics. By leveraging LLM to interpret verbal task descriptions, we aim to capture subtle distinctions in routineness and cognitiveness that may be challenging to quantify through traditional methods.

Our novel methodology, while promising, is not without limitations. The primary concern lies in the reliability of LLM’s output. Although this issue is likely to diminish in significance given the rapid advancements in LLM technology, it

is important to note that the decision-making process is entirely delegated to the LLM. A secondary concern pertains to replicability. Due to the inherent variability in LLM outputs across iterations, the generated values, while similar, are not precisely identical. This variability poses challenges for exact reproduction of results. The third concern involves temporal relevance. Our study is well-suited for examining recent routineness, which has a close relationship with automation. However, the determination of routineness is based on current technological standards. Consequently, this methodology may not be appropriate for studying pre-2000s routineness patterns.

To address the aforementioned reliability concerns, we employ a dual-model approach, utilizing two state-of-the-art LLMs: OpenAI’s GPT-4 and Anthropic’s OPUS-3. While other advanced models exist, such as Anthropic’s Sonnet-3.5, Meta’s Llama-3, and Google’s Gemini, current consensus in the field suggests that OPUS-3 and GPT-4 represent the pinnacle of LLM capabilities. This approach leverages the strengths of both models to enhance the robustness of our methodology.

## 2. Definitions and Commands

### 2.1. Definitions

In the literature, universal definitions for *routineness* and *cognitiveness* do not exist (Haslberger, 2022). Each study uses distinct definitions. Therefore, we define these terms by referring to many existing studies (Cortes et al., 2017; Haslberger, 2022; Fernández-Macías et al., 2023). The definitions that we incorporated into the Python code to measure RTI-LLM and CTI-LLM are as follows:

**A routine task** involves activities that are predictable and can be automated, such as those performed by industrial robots on assembly lines or through computerization. This typically involves substituting human labor for routine information processing or repetitive tasks. **A non-routine task** requires handling unpredictable situations or resolving exceptions that automated systems and programs cannot adequately address. Examples include caregiving, creative writing, or artistic activities that demand human intuition and creativity.

**A cognitive task** involves activities that require mental processes, skills, and abilities. These include perception, thinking, reasoning, memory, learning, decision making, and other aspects of information processing. Examples of cognitive tasks are problem-solving, language comprehension, attention, and pattern recognition. **A manual task** involves physical processes, activities, and

skills. These require the use of hands, the body, and sensory-motor coordination, including dexterity, precision, physical effort, and manipulation of tools or objects. Examples of manual tasks include handwriting, using tools, playing an instrument, and assembly work.

## 2.2. *Commands*

The commands below are the actual instructions that we used in the Python code to instruct the LLMs.

### 2.2.1. *Routiness*

**Extremely Non-Routine Task (Score: 0):** Assign a value of 0 exclusively to tasks that necessitate human creativity, intuition, or involve complex, unpredictable problem solving that cannot be replicated by current automation technologies at all.

**Extremely Routine Task (Score: 1):** Assign a value of 1 only to tasks that are fully automatable with absolutely no need for human discretion or unpredictable judgment. This should be strictly limited to tasks where current technology can perform the task without any human oversight.

**Moderately Routine or Non-Routine Tasks (Score range: 0.3 to 0.7):** Assign values within this range to tasks that blend elements of both routine and non-routine characteristics, or when the classification into extreme categories is not clear. The middle range should be expanded slightly to encourage less extreme scoring, using 0.5 as a central point for truly ambiguous tasks.

**Uncertainty Principle:** If there is any uncertainty in classifying the task, default to a score closer to 0.5. Use the wider range of 0.3 to 0.7 to adjust the score slightly if there is a mild inclination towards routine or non-routine characteristics. This approach should ensure that only tasks with clear and definitive characteristics receive scores at the extremes.

**Output Format:** Begin your response with the score, followed by a colon and a detailed explanation of your reasoning. The explanation should thoroughly consider the task's characteristics, including the potential for automation and the level of human input or creativity required.

### 2.2.2. *Cognitivity*

**Extremely Manual Task (Score: 0):** Assign a value of 0 only to tasks that are fully manual task.

**Extremely Cognitive Task (Score: 1):** Assign a value of 1 exclusively to tasks

are full cognitive task.

**Moderately Manual or Cognitive Tasks (Score range: 0.3 to 0.7):** Assign values within this range to tasks that blend elements of both manual and cognitive characteristics, or when the classification into extreme categories is not clear. The middle range should be expanded slightly to encourage less extreme scoring, using 0.5 as a central point for truly ambiguous tasks.

**Uncertainty Principle:** If there is any uncertainty in classifying the task, default to a score closer to 0.5. Use the wider range of 0.3 to 0.7 to adjust the score slightly if there is a mild inclination towards manual or cognitive characteristics. This approach should ensure that only tasks with clear and definitive characteristics receive scores at the extremes.

**Output Format:** Begin your response with the score, followed by a colon and a detailed explanation of your reasoning. The explanation should thoroughly consider the task’s characteristics.

### 3. Scoring Results

We provide a full set of results in the Stata format at the link provided in the footnote.<sup>1</sup> This file includes task code, task description, routine score, cognitive score, and their corresponding reasonings. The dataset contains 23,825 observations (tasks). Using the task code, researchers can merge this information with any O\*NET data. An example is shown as follows, and we provide only one example to conserve space. This study employed two LLMs, namely GPT-4 and OPUS-3, to quantify the dimensions of routineness and cognitive complexity in task analysis.

#### 3.1. Example

**Task description:** Resolve customer complaints regarding sales and service.

**OPUS Routine score:** 0.4

**OPUS Routine reasoning:** Resolving customer complaints regarding sales and service involves a blend of routine and non-routine elements. While some aspects of the task, such as documenting complaints or following standardized resolution procedures, can be considered routine and potentially automatable, the core of the task requires human interaction, empathy, and problem-solving

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<sup>1</sup><https://tinyurl.com/yc8nu4t7>

skills. Customer complaints often involve unique situations that demand active listening, understanding the customer's perspective, and finding creative solutions to address their concerns. Each complaint may present a different challenge that requires adapting to the specific context and using human judgment to determine the most appropriate course of action. However, the task is not entirely non-routine, as there are likely established guidelines.

**GPT Routine score:** 0.3

**GPT Routine reasoning:** Resolving customer complaints regarding sales and service is predominantly a non-routine task. While certain aspects of customer service can be automated, such as providing information about services or products, handling complaints often involves unpredictable elements and requires human intuition and creativity. Each customer complaint is unique and may require a different approach or solution, which is challenging to automate. The task involves understanding the customer's emotions, empathizing with them, and devising solutions to their problems, which are skills that are currently beyond the capabilities of automation technologies. However, since some aspects of the task, such as gathering initial information about the complaint, can be automated, it does not fully qualify as an extremely non-routine task.

**OPUS Cognitive score:** 0.8

**OPUS Cognitive reasoning:** Resolving customer complaints regarding sales and service is primarily a cognitive task. It involves several mental processes and skills, such as: 1. Communication and language comprehension: Understanding the customer's complaint and effectively communicating with them to gather information and provide solutions. 2. Problem-solving and decision-making: Analyzing the complaint, identifying the root cause of the issue, and determining the most appropriate course of action to resolve the problem. 3. Empathy and emotional intelligence: Being able to understand and relate to the customer's feelings and concerns, while maintaining a professional and composed demeanor. 4. Knowledge application: Utilizing knowledge of the company's products, services.

**GPT Cognitive score:** 0.8

**GPT Cognitive reasoning:** The task of resolving customer complaints regarding sales and service is primarily a cognitive task. It involves understanding the customer's problem (language comprehension), thinking of the best way to resolve the issue (problem-solving, decision making), and communicating that solution effectively (language comprehension again). It may also involve recalling relevant information about the company's policies or the customer's past transactions (memory). However, there might be some manual aspects involved

such as typing responses or navigating through the customer service software, which is why the task doesn't score a full 1. The cognitive aspects of this task clearly outweigh the manual ones, hence the score leans more towards the cognitive end of the scale.

### 3.2. Scatter Plot of RTI and CTI

Since we have used both GPT-4 and OPUS-3, we can provide a scatter plot as shown below. Figure 1 presents a comparative analysis of routineness and cognitiveness scores for GPT-4 and OPUS-3. The visualization reveals several data points exhibiting inconsistencies between the two models' respective scores. We decide to incorporate these inconsistent scores as well as consistent scores by calculating the mean of the scores generated by two distinct Large Language Models: GPT-4 and OPUS-3.

Kernel density plots for the averaged scores of RTI and CTI are presented in Panels (c) and (d) of Figure 1, respectively. An analysis of these plots reveals distinct distributions for routine and cognitive task intensities across occupations. From a routine perspective, the distribution of RTI (Routine Task Intensity) indices demonstrates a pronounced concentration in the lower range (0.2-0.4), indicating that occupations with low routine task intensity comprise the largest proportion of the sample. Conversely, the distribution of CTI (Cognitive Task Intensity) indices exhibits a bimodal pattern. While occupations with high CTI indices (0.6-0.9) predominate, there is also a substantial cluster of occupations with low CTI indices (0.2-0.3).

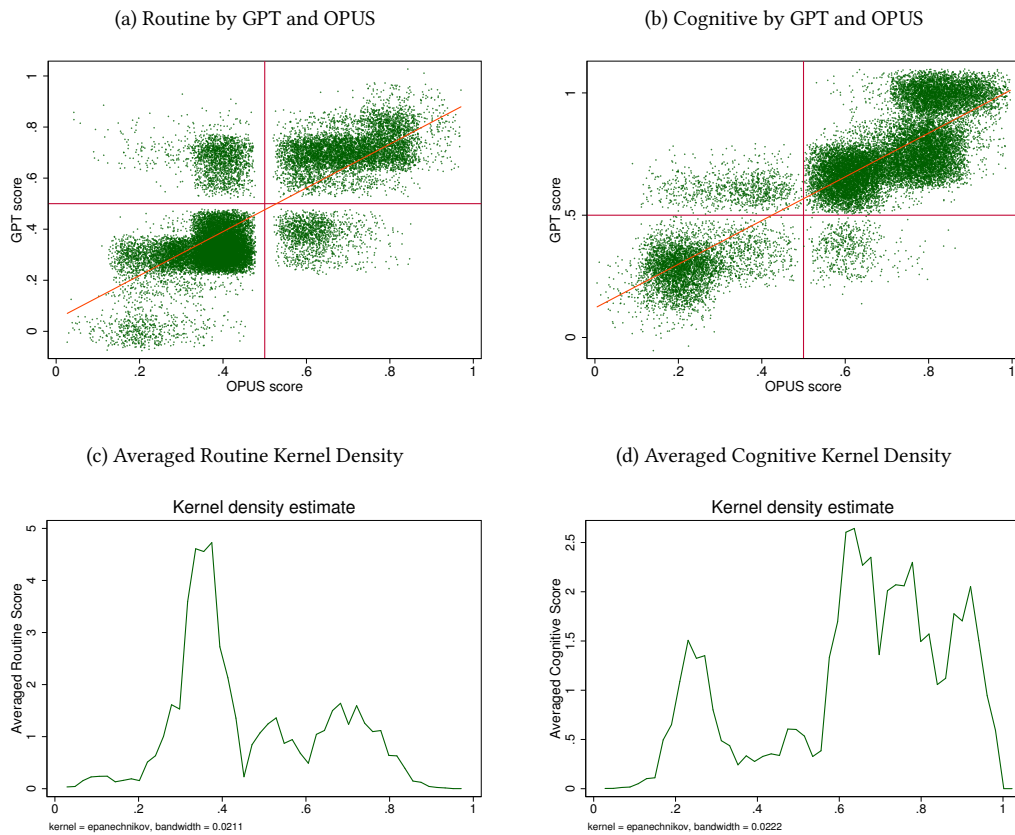
The justification for employing the mean of the scores generated by GPT-4 and OPUS-3 is predicated on the following rationale. As elucidated in Section 3.2.1, the inconsistency primarily arises due to the nature of tasks that are susceptible to subtle scoring variations based on perspective and viewpoint. Consequently, if we were to calculate the average of these inconsistent data points, which are situated in the second and fourth quadrants, we would obtain values approximating 0.5. We posit that this computational method is appropriate, as it reflects the inherent ambiguity in the original task descriptions, which were challenging to evaluate definitively.

We provide an example of these inconsistencies to explain why the two LLMs for routine score have different opinions. (For the sake of conciseness, the subsection demonstrating inconsistencies in cognitive assessment scores will be provided in [Appendix A](#).) OPUS-3 placed more emphasis on the non-routine aspects of the task, such as the need for human judgment and creativity in layout design



and typography instructions. GPT-4, in contrast, focused more on the routine elements, such as marking up and pasting layouts, while acknowledging the presence of some non-routine components. The two measures may have interpreted the task description differently, leading to varying assessments of the routine and non-routine aspects involved. GPT-4 and OPUS-3 likely employ different algorithms and training data to assess the routine nature of tasks, which could result in divergent scores. In summary, the discrepancy in scores between GPT-4 and OPUS-3 can be attributed to their different interpretations of the task, the weighing of routine and non-routine elements, and the underlying differences in their algorithms and training data.

Figure 1: Routine and Cognitive Scores



### 3.2.1. Inconsistent Example

**Task description:** Mark up, paste, and complete layouts and write typography instructions to prepare materials for typesetting or printing.

**OPUS Routine score:** 0.4

**OPUS Routine reasoning:** The task of marking up, pasting, and completing layouts, as well as writing typography instructions for typesetting or printing, involves a combination of routine and non-routine elements. Routine aspects: Some parts of the layout process may be predictable and follow established templates or guidelines. Certain typography instructions might be standardized based on the type of material being prepared. Non-routine aspects: The specific content and design requirements for each layout may vary, requiring human judgment and creativity to ensure the final product meets the desired aesthetic and communicative goals. Writing typography instructions may involve considering the unique characteristics of the material and making decisions based on factors.

**GPT Routine score:** 0.7

**GPT Routine reasoning:** This task involves a mixture of both routine and non-routine characteristics. While aspects of the task, such as marking up and pasting layouts, can potentially be automated, the need for writing typography instructions suggests a level of human discretion and creativity. The judgment involved in deciding the appropriate typography for a given material is not easily replicable by current automation technologies, suggesting a non-routine characteristic. However, given that the bulk of the task appears to be routine in nature, with only a portion requiring human input, a score slightly leaning towards routine (0.7) is assigned. The score is not at the extreme end of the routine scale due to the presence of some non-routine elements.

## 4. Comparative Analysis of Routine and Cognitive Task

This section examines the levels of routineness and cognitiveness in occupations. As shown in Panel (a) of Figure 2, occupations at the six-digit SOC level can be categorized into four dimensions: (1) routine cognitive, (2) routine manual, (3) non-routine cognitive, and (4) non-routine manual. Furthermore, Panel (b) of Figure 2 presents RTI-LLM and CTI-LLM measurements at the SOC 2-digit level. In this figure, x-axis is our RTI-LLM, and y-axis is our CTI-LLM. As one might expect, ‘management’ and ‘legal’ occupations are highly cognitive and non-routine, while ‘production’ and ‘construction’ occupations are highly

manual and routine.

It is important to note that each occupation comprises several tasks —typically ranging from ten to thirty, for instance. When calculating the routineness and cognitiveness values, tasks are weighted differently: those labeled as ‘core’ by O\*NET are given a weight of 5, while those labeled as ‘supplementary’ are assigned a weight of 1. An illustrative example distinguishing between core and supplementary elements is presented in [Appendix B](#).

#### 4.1. Correlation with other RTI Measures

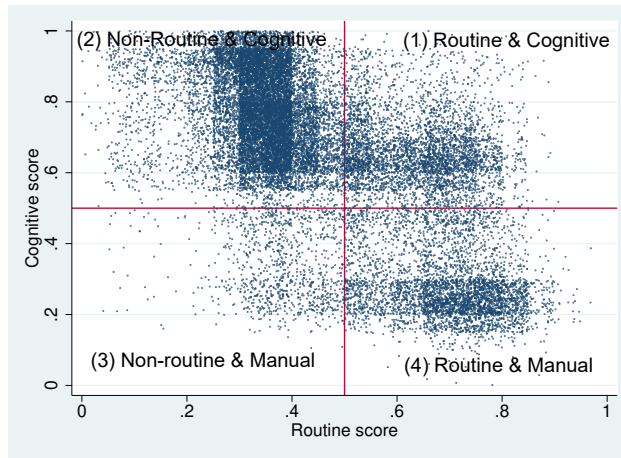
Expanding upon the correlation matrix presented by [Walo \(2023\)](#), we incorporated our RTI-LLM as an additional variable. While maintaining the original values reported by [Walo \(2023\)](#), we augmented the matrix by one row and one column to accommodate our novel measure (Table 1). The replication dataset, constructed by [Walo \(2023\)](#), comprises 74 semi-broad occupations categorized according to the OCC1990 classification system. Our study adheres to this occupational framework. Each of the 74 occupations is assigned a unique RTI value, independently derived by various studies. Consequently, we examined the correlations between these diverse studies’ RTI measures. The observed correlational patterns for the RTI-LLM demonstrate congruence with the convergent validity criteria, a concept elucidated by [Walo \(2023\)](#). This principle examines the degree to which distinct measures exhibit mutual correlation. These findings suggest that the RTI-LLM demonstrates suitable associations with conceptually related constructs, thereby providing evidence for its validity as a measure of routine task intensity.

Table 1: Correlation table between RTI indicators

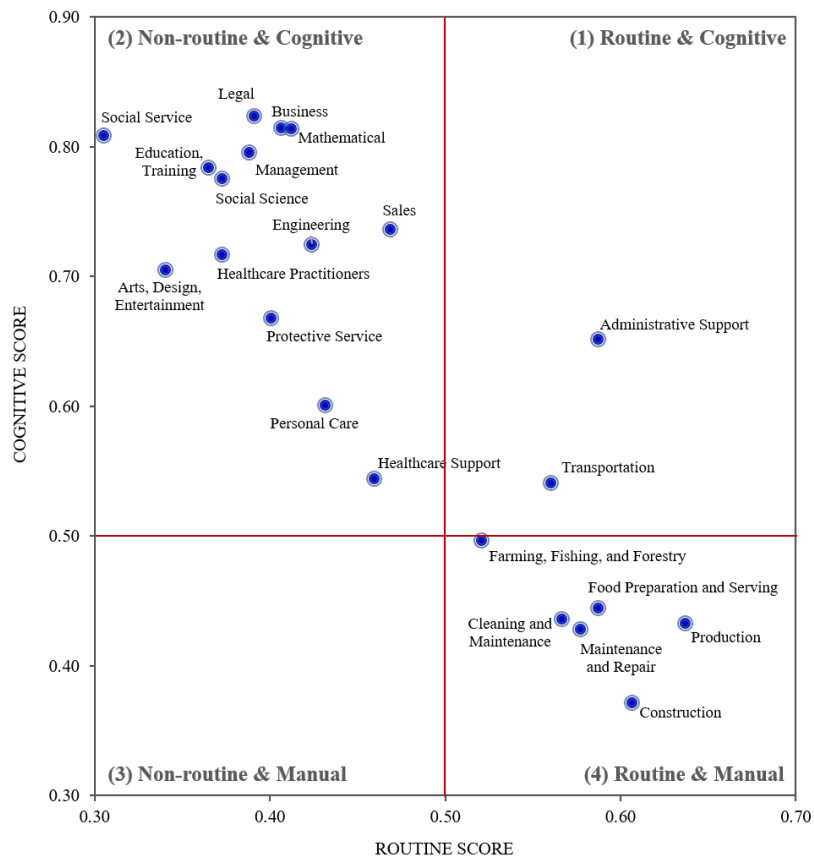
	Emp Share (1980–2005)	RTI Autor et al.	RTI Acemoglu	RTI Goos et al.	RTI Dengler	RTI Marcolin	RTI LLM
<b>Employment Share</b>	<b>1.00</b>						
<b>RTI Autor et al.</b>	-0.35	<b>1.00</b>					
<b>RTI Acemoglu</b>	-0.42	0.38***	<b>1.00</b>				
<b>RTI Goos et al.</b>	-0.35	-0.08	0.68***	<b>1.00</b>			
<b>RTI Dengler</b>	-0.50	0.32***	0.58***	0.68***	<b>1.00</b>		
<b>RTI Marcolin</b>	-0.33	0.05	0.59***	0.73***	0.44***	<b>1.00</b>	
<b>RTI-LLM</b>	-0.46	0.37***	0.76***	0.71***	0.64***	0.66***	<b>1.00</b>

Figure 2: Cognitive Score vs Routine Score

(a) SOC 6-digit Level



(b) RTI-LLM and CTI-LLM using SOC 2-digit



#### 4.2. Comparative Analysis with [Autor and Dorn \(2013\)](#)'s Work

Remember that [Autor and Dorn \(2013\)](#)'s RTI measure is calculated by using three variables as shown in Equation (1). This approach to quantifying routine task intensity provides a comprehensive view of occupational characteristics.

$$\text{RTI} = \ln(\text{Routine}) - \ln(\text{Manual}) - \ln(\text{Abstract}) \quad (1)$$

Accordingly, we conduct a simple regression exercise using these three variables as follows.

$$\text{RTI-LLM} = \alpha_0 + \alpha_1 \ln(\text{Routine}) + \alpha_2 \ln(\text{Manual}) + \alpha_3 \ln(\text{Abstract}) + \varepsilon$$

The regression results are presented in Table 2. A notable aspect of this result is that the 'Manual' variable appears to be irrelevant to RTI-LLM measure. It is important to emphasize that this discrepancy does not imply that either approach is definitively correct or incorrect.

Table 2: Regressions

	Y=RTI-LLM
ln(Routine)	0.074*** (0.011)
ln(Manual)	-0.002 (0.004)
ln(Abstract)	-0.100*** (0.007)
<i>N</i>	210
<i>R</i> <sup>2</sup>	0.566

Standard errors in parentheses

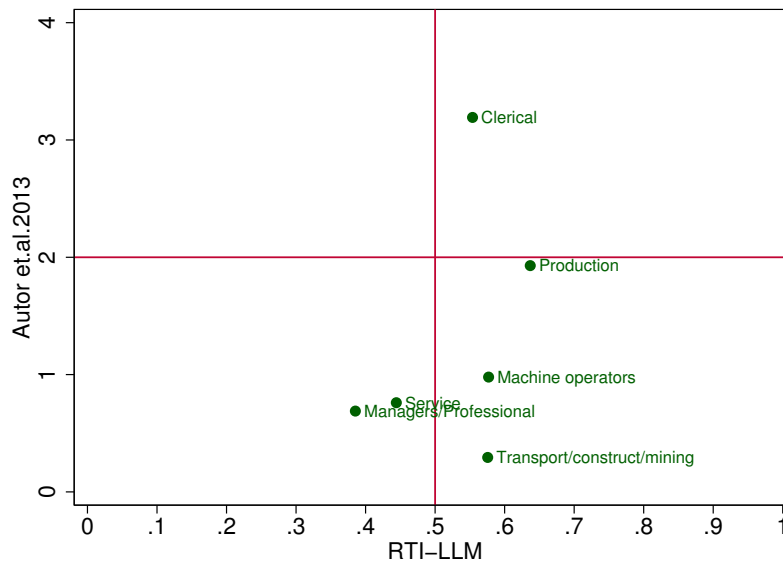
\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Meanwhile, a notable finding from our analysis is that the signs of coefficients are all consistent with those used by [Autor and Dorn \(2013\)](#) in Equation (1). This consistency suggests that despite the differences in our methodologies, there is a fundamental alignment in how various factors contribute to the measure of routine task intensity. This alignment lends credibility to both approaches while highlighting the robustness of these relationships across different analytical frameworks.

Regarding [Autor and Dorn \(2013\)](#)'s RTI measure, a pertinent question arises: Is it not sufficient to include only the Routine variable as an explanatory factor in their RTI measure, given that it inherently captures the essence of routine itself? However, it is crucial to note that the term 'Routine' in this context diverges from its common dictionary definition, as well as those employed in the DOT. Specifically, for the purpose of this analysis, the concept of 'Routine' must encompass not only the susceptibility to automation but also the repetitive nature of the tasks involved. [Haslberger \(2022\)](#) provides a comprehensive discussion on the nuances and complexities surrounding the definition of this term in the context of labor market research.

Figure 3 presents a comparison of RTI measures between our study and that of [Autor and Dorn \(2013\)](#). The results indicate no positive correlation between the two sets of measures. Notably, the 'service' occupation category, which emerges as a crucial element in the subsequent section, exhibits a significant disparity. While both our study and [Autor and Dorn \(2013\)](#)'s classify 'service' within the non-routine domain, our measure positions it as nearly neutral, whereas [Autor and Dorn \(2013\)](#)'s assessment places it more definitively in the non-routine spectrum.

Figure 3: Routine Score Comparison



### 4.3. Comparison with Cortes et al. (2014)'s Work

Cortes et al. (2014) employed a classification system based on the Standard Occupational Classification (SOC) taxonomy to categorize occupations into four distinct groups. Their categorization is summarized in Table 3.

Table 3: Cortes et al. (2014)'s Occupational Classification

	Routine	Non-routine
Cognitive	Sales and Office	Management, Science. etc
Manual	Construction;Maintenance;Production	Service

Our findings, as presented in Table 4, offer a categorization that differs from previous research. A notable distinction between our classification and that of Cortes et al. (2014) is the categorization of 'service' tasks. In our analysis, 'service' is not classified under manual tasks, contrary to their approach.

Table 4: Occupational Classification based on RTI-LLM and CTI-LLM

	Routine	Non-routine
Cognitive	Sales and Office	Management, Science. etc; Service
Manual	Construction;Maintenance;Production	

## 5. Longitudinal Analysis

This section presents a concise overview of the time-series patterns observed in our routine and cognitive measures. Our analysis elucidates the evolution of these occupational characteristics over time. The cornerstone of our longitudinal investigation is the examination of employment share distributions across four distinct categories: (1) routine-cognitive, (2) non-routine cognitive, (3) non-routine manual, and (4) routine-manual. In Figure 4, 'Total Occupation' graphically represents these trends, with the blue line denoting 'Manual' (i.e., non-cognitive) occupations and the dotted line indicating 'Routine' occupations. The visualization reveals a well-established pattern that demonstrates anticipated congruence with the findings presented by Vom Lehn (2020). Notably, irrespective of the cognitive dimension, a consistent and pronounced decline in the proportion of routine occupations is evident. The persistent nature of this diminution in routine job shares suggests a fundamental transformation in

the landscape of work, potentially driven by technological advancements and evolving economic structures.

To elucidate this phenomenon further, we analyze supplementary panels within the same figure, which are analogous to the preceding one but focus discretely on specific occupational categories. These granular visualizations unveil a critical distinction: while most occupational groupings, including ‘production’, demonstrate relatively consistent patterns, it is the ‘service’ and ‘sales (clerk)’ categories that exhibit the most pronounced fluctuations. This observation corroborates the emphasis placed by [Autor and Dorn \(2013\)](#) on the pivotal role of service occupations in shaping contemporary labor market dynamics. The distinctive trajectory of service occupations suggests that this sector may be instrumental in elucidating the sustained decline in routine job shares beyond the year 2000.

Moreover, the ‘sales (clerk)’ occupation category, in addition to ‘service’, demonstrates a notable shift in its compositional structure—an aspect overlooked in [Autor and Dorn \(2013\)](#)’s analysis. Following our examination of the ‘service’ category, we will proceed to conduct a comparable analysis of the ‘sales’ occupation.

### *5.1. Analysis of Service Occupation*

The proportion of employment in non-routine cognitive tasks within the ‘service’ occupation category has exhibited a steady increase from 1970 to the present. This trend aligns with the within-occupation changes highlighted by [Fernández-Macías et al. \(2023\)](#). We disaggregated the broad category of service occupations into five distinct subcategories: Healthcare support, Protective service, Food preparation and serving, Cleaning and maintenance, and Personal care. This detailed classification allowed us to conduct a nuanced analysis of the trends observed in Panel (a) of Figure 5, which replicates Panel (c) of Figure 4 for ease of reference. Specifically, we sought to elucidate the underlying factors contributing to the persistent decline in routine Manual employment share and the concurrent increase in non-routine cognitive employment share.

To investigate the causes of the steady decline in routine manual employment share, we first examined the absolute employment size by detailed occupation, as illustrated in Panel (a) of Figure 6. This analysis revealed that Food preparation and serving, along with Cleaning and maintenance, constitute the majority of employment in absolute terms. Figure 5 clearly demonstrates that both of these occupational categories have experienced a consistent decrease in routine manual employment share. Consequently, we posit that these two occupational



Figure 4: Employment Share by Occupations

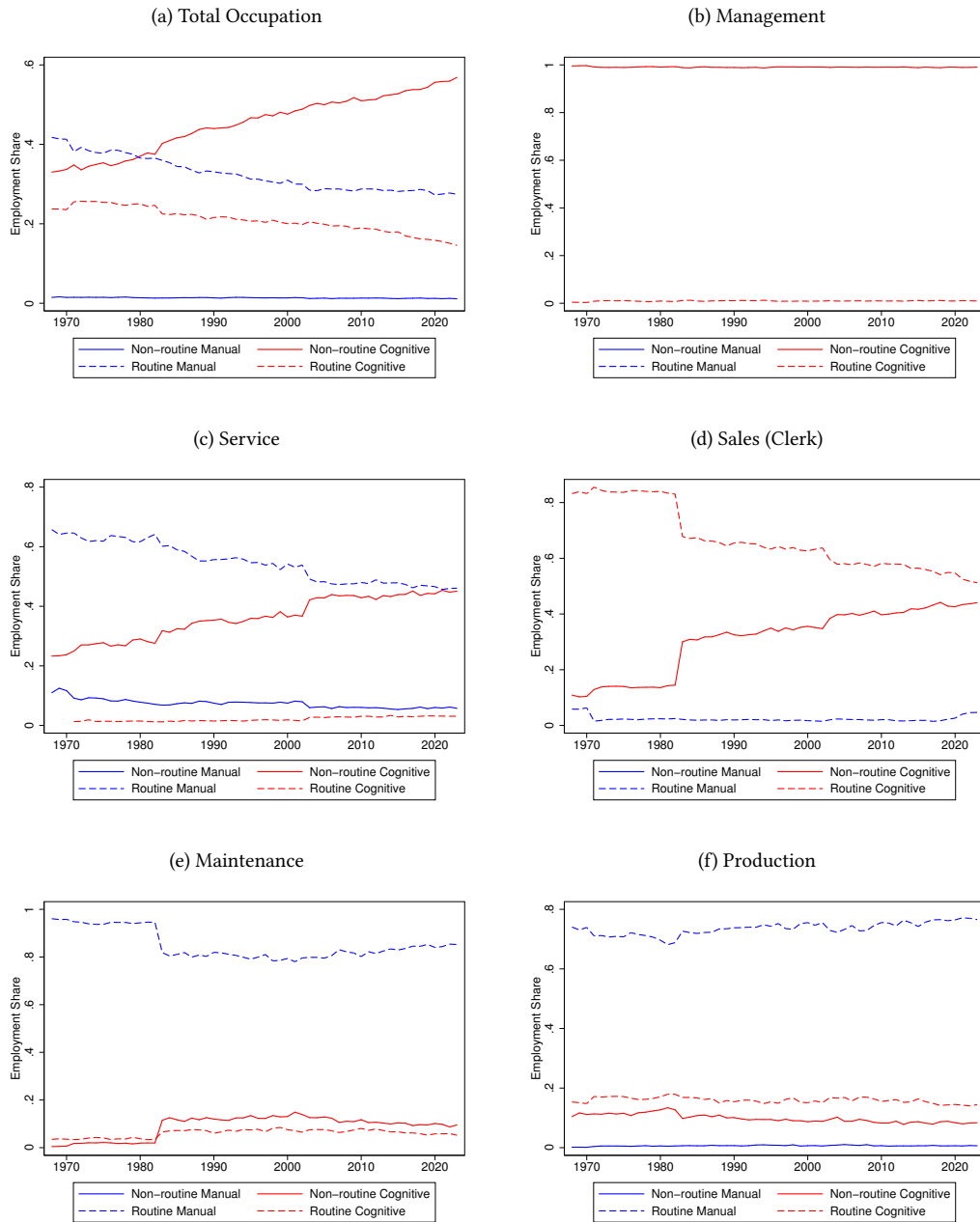


Figure 5: Employment Share in Detailed Service Occupation

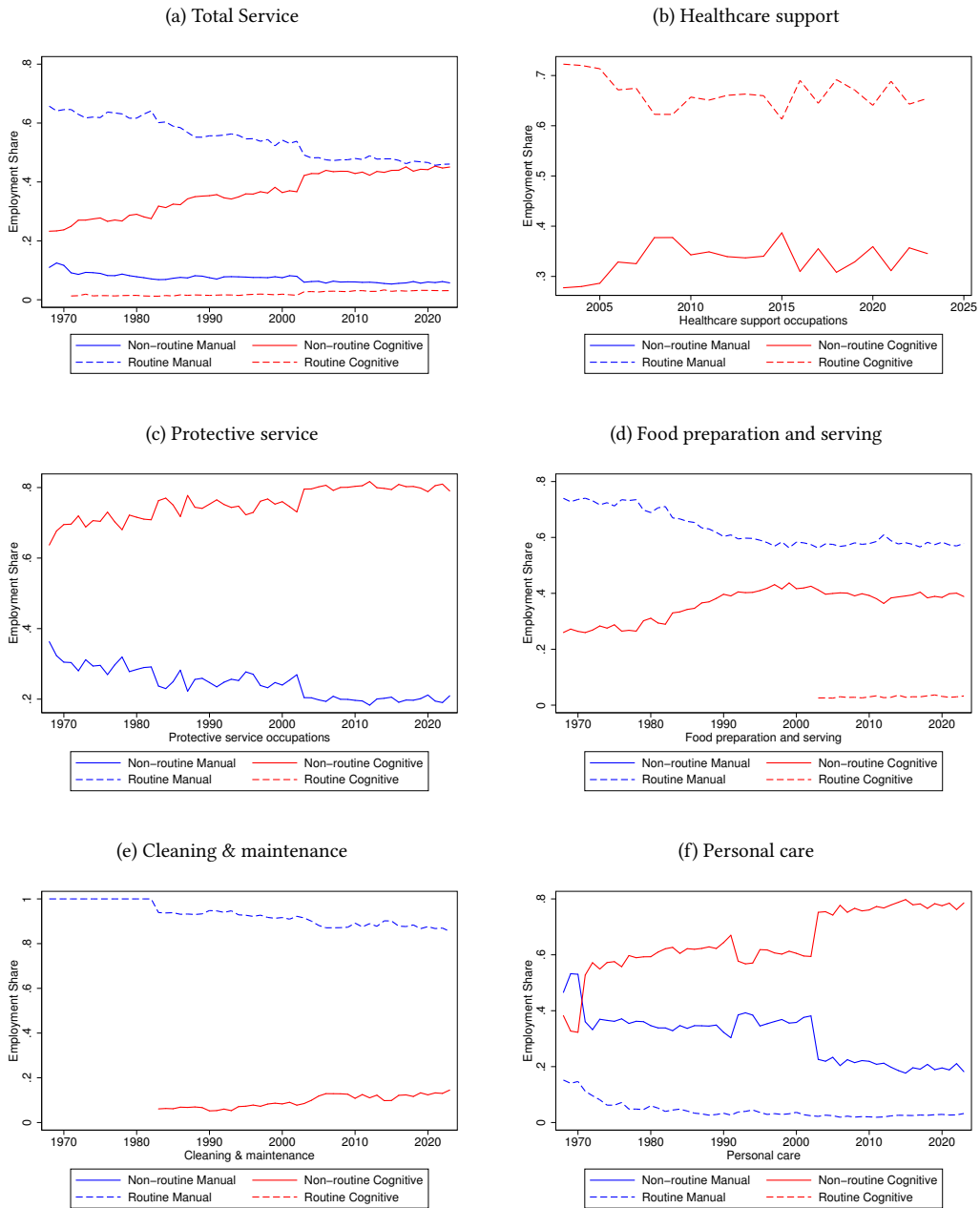
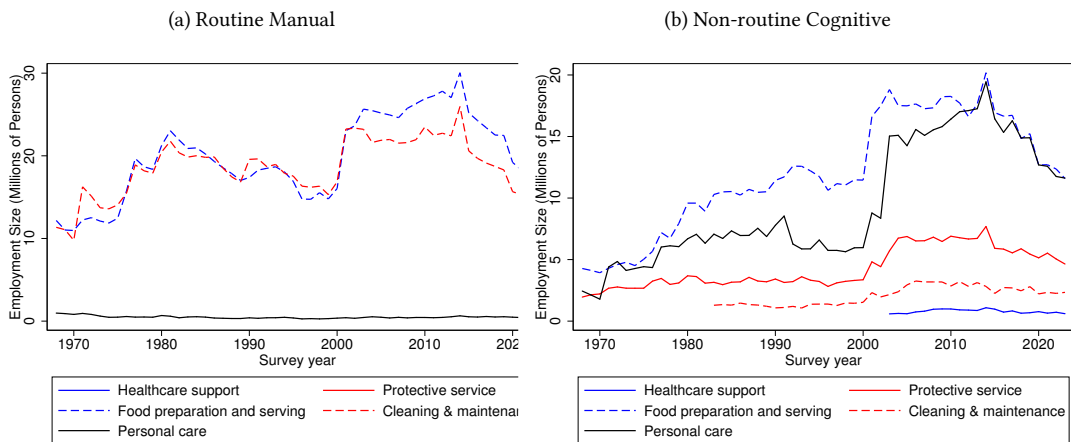


Figure 6: Employment Size



groups are the primary drivers of the observed decline in routine manual employment share.

Regarding the steady increase in non-routine cognitive employment share, we similarly analyzed the absolute employment size by detailed occupation, as depicted in Panel (b) of Figure 6. This examination indicated that Food preparation and serving, as well as Personal care, represent the largest proportion of employment in absolute terms, with Protective service also comprising a notable portion. Figure 5 clearly illustrates that both Food preparation and serving and Personal care have exhibited a consistent rise in non-routine cognitive employment share. Thus, we conclude that these two occupational categories are the principal contributors to the observed increase in non-routine cognitive employment share. This refined analysis provides valuable insights into the specific occupational dynamics underlying the broader trends in employment share across task categories.

### 5.1.1. Testing *Autor and Dorn (2013)*'s Hypothesis of Job Polarization

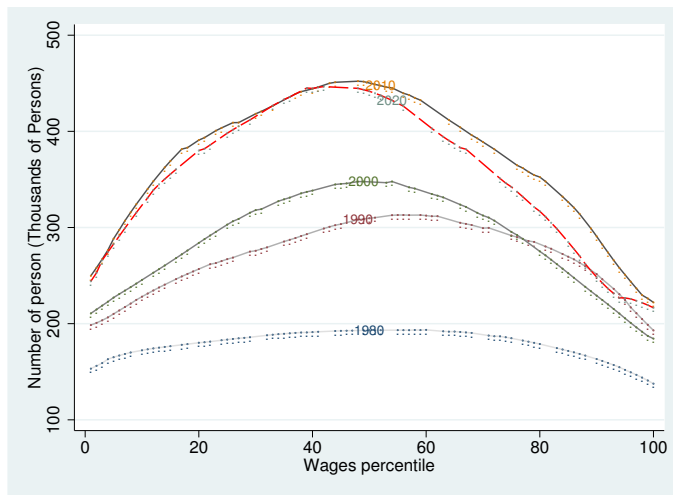
The job polarization hypothesis, as proposed by *Autor and Dorn (2013)*, suggests that workers in middle-skill occupations (using wages as a proxy for skill level) are predominantly transitioning to service-sector jobs. This concept aligns with the theoretical framework initially articulated by *Fernández-Macías and Hurley (2017)*, which posits that the decline in middle-skilled occupations is driving a shift towards non-routine service roles. If this hypothesis holds true, we would expect Figure 7 to display an inverted U-shaped distribution. Such a

pattern would indicate a disproportionate movement of middle-wage workers into service occupations, thus lending support to the job polarization narrative.

For each decennial period, we enumerate individuals within each wage percentile prior to their transition into the service occupation. It is crucial to emphasize that the wage metric utilized in this analysis does not reflect current remuneration within the service occupation, but rather the compensation associated with the individual's previous non-service occupation. This methodological approach aims to elucidate the socioeconomic characteristics of individuals migrating to the service occupation. To elaborate, for each wage percentile, we compute the aggregate number of individuals who transitioned from non-service to service occupations.

Figure 7 illustrates our findings, revealing an inverted U-shaped distribution consistently across all decades examined. Notably, this phenomenon appears to be intensifying in recent years. The persistence and intensification of this trend could be due to more advanced computerization and robotic technologies continuing to evolve, or it may indicate other structural changes within society.

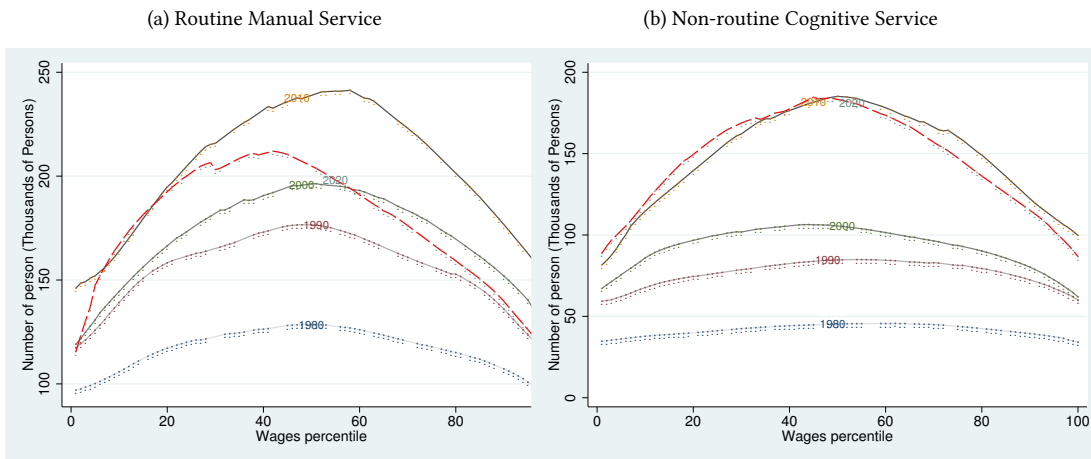
Figure 7: Wages before transitioning from non-service industries to the service industry



We conducted an additional exercise similar to that presented in Figure 7, but with a focus on two specific categories: 'routine manual' and 'non-routine cognitive' occupations. In this analysis, we compiled data on individuals' wages prior to their transition from non-service occupations to either 'routine manual' service occupations or 'non-routine cognitive' service occupations. The results of this analysis are depicted in Figure 8. Both panels in Figure 8 exhibit inverted

U-shaped patterns, which appear to be intensifying as we approach more recent years. This trend suggests a growing importance or prevalence of service occupations in the polarization trend of the labor market.

Figure 8: Wages before transitioning from non-service industries to the service industry



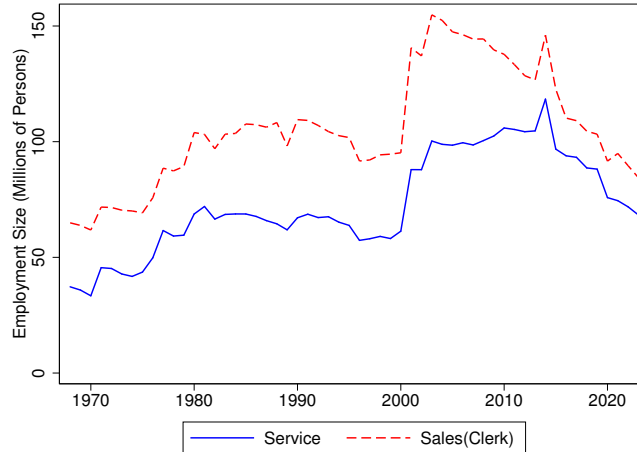
## 5.2. Analysis of Sales(Clerk) Occupation

As illustrated in Figure 9, the employment magnitude within the sales occupation is comparable to that of the service occupation, indicating its significant presence in the labor market. Furthermore, Panel (d) of Figure 4 demonstrates substantial shifts in the routineness and cognitive demands within sales occupations. Despite these notable trends, there has been a relative paucity of academic attention devoted to the sales occupation in existing literature. This subsection aims to address this gap by focusing specifically on sales occupations.

In contrast to the service occupation, the sales domain exhibits distinct patterns of change. Panel (d) of Figure 4 reveals a decline in routine-cognitive tasks, concurrent with an increase in non-routine-cognitive activities. We posit that this transformation within Sales is a primary contributor to the consistent decrease in routine-cognitive tasks observed across ‘Total Occupation’ categories, as depicted in Panel (a) of Figure 4.

To delve deeper into this phenomenon, we have adopted an analytical approach similar to that employed in Subsection 5.1.1. Our methodology involves scrutinizing the wage histories of individuals who transitioned from various occupations into sales roles. Specifically, we examine the wage percentiles of

Figure 9: Employment Size between Service and Sales Occupation

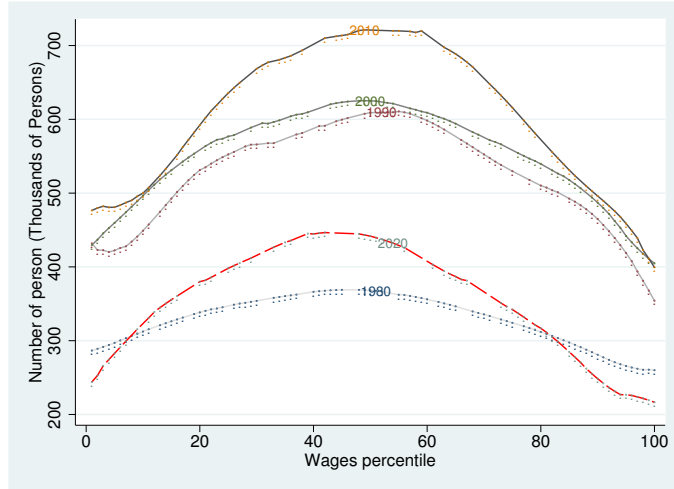


these individuals in their previous non-sales positions for each ten-year period. It is crucial to emphasize that the wage data used in this analysis pertains to the individuals' former occupations, not their current earnings within the sales occupation.

The findings presented in Figure 10 offer an additional perspective to the existing job polarization literature. The job polarization hypothesis, as articulated by Autor and Dorn (2013), posits that workers with mid-level skills are predominantly shifting towards service-oriented roles, suggesting that the service occupation is a primary driver of job polarization. Our analysis, as depicted in Figure 10, complements this view by indicating that the sales occupation may also play a significant role in driving this polarization trend. This observation expands upon the existing framework, suggesting that multiple occupational categories, including both service and sales, may contribute to the observed labor market dynamics.

The sales occupation is predominantly categorized into two distinct subgroups: 'Sales and related' and 'Office and administrative support' (commonly referred to as clerical roles). We applied the aforementioned analytical methodology to these subcategories. The resultant findings are presented in Figure 11. Notably, both subcategories exhibit an inverted U-shaped distribution, mirroring the pattern observed in the aggregate data. This observation carries significant implications, suggesting that the phenomenon of job polarization is not solely attributable to the service occupation, as previously postulated. Rather, the sales occupation,

Figure 10: Wages before transitioning from non-sales to the sales

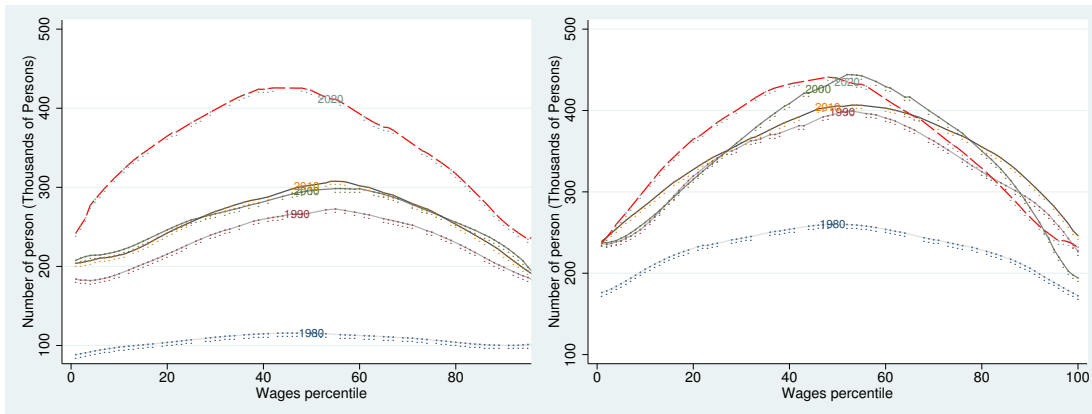


encompassing both 'Sales and related' roles and 'Office and administrative support' positions, appears to be a substantial contributor to this labor market trend.

Figure 11: Wages before transitioning

(a) From non-'Sales and related' to the 'Sales and related'

(b) From non-'Clerk' to the 'Clerk'



## 6. Regression Analysis

We conduct a series of regressions based on Equation (2) using yearly IPUMS CPS (Flood et al., 2023), from 1969 to 2023, to assess the relative importance of routineness and cognitive scores in wage determination. The dependent variable in our model is the real wage, which has been adjusted for inflation using the Consumer Price Index (CPI). Specifically, this wage metric represents the respondent’s total pre-tax wage and salary income for the preceding calendar year.

A critical methodological consideration in this analysis pertains to the temporal context of the wage variable. The wage data utilized in our regression model reflects the remuneration associated with the respondent’s current occupation, rather than their previous employment. Consequently, this analytical framework enables us to assess the contemporary impact of routine and cognitive factors on wage determination. This distinction is crucial, as it allows for the evaluation of how these factors influence present-day compensation structures, rather than historical wage patterns.

To facilitate trend comparisons, we incorporate interaction terms between yearly dummy variables ( $D_y$ )<sup>2</sup> and both routineness and cognitive scores. Base dummy year is 1970. The model includes control variables for states, age, industry, and education level, all treated as categorical dummy variables, except age. To account for serial correlation, standard errors are clustered at the state level. These regressions are performed separately for each occupation-sex group. Observations are at the individual level; therefore, both routine and cognitive scores are raw scores that continuously range from 0 to 1.

$$\ln(\text{wage}) = D_y \times \text{routine score} + D_y \times \text{cognitive score} + \gamma X + \varepsilon \quad (2)$$

Given the complexity introduced by the presence of dummy coefficients, discerning meaningful patterns from the tabular data presents significant challenges. To address this issue and enhance interpretability, we have transformed the data into a graphical format, as illustrated in Figure 12. Each data point in this visualization represents an aggregation of the base coefficient and its

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<sup>2</sup>D\_year:1970 if actual years are between 1969 and 1979, D\_year:1980 if actual years are between 1980 and 1989, D\_year:1990 if actual years are between 1990 and 1999, ... and D\_year:2010 if actual years are between 2010 and 2023.



Table 5: Regressions

	MANAGEMENT		SERVICE		SALES		MAINTENANCE		PRODUCTION	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sex	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Routinescore	-0.825*** (0.124)	-0.896*** (0.104)	1.228*** (0.127)	1.146*** (0.086)	-0.008 (0.059)	0.871*** (0.045)	-0.557*** (0.079)	-1.434*** (0.430)	-0.237*** (0.085)	0.115 (0.129)
Routine-1980	0.211 (0.142)	0.207** (0.103)	-0.088*** (0.033)	-0.070 (0.045)	-0.201*** (0.032)	-0.446*** (0.047)	-0.425*** (0.051)	-0.066 (0.306)	-0.175*** (0.018)	-0.103*** (0.027)
Routine-1990	0.046 (0.141)	0.282*** (0.092)	-0.031 (0.038)	-0.075 (0.050)	-0.439*** (0.047)	-0.614*** (0.038)	-0.515*** (0.069)	-0.055 (0.313)	-0.306*** (0.023)	-0.148*** (0.038)
Routine-2000	-0.205 (0.161)	0.186* (0.103)	-0.078** (0.035)	-0.002 (0.047)	-0.623*** (0.038)	-0.573*** (0.040)	-0.425*** (0.058)	0.408 (0.302)	-0.243*** (0.026)	-0.033 (0.033)
Routine-2010	-0.241 (0.175)	0.056 (0.098)	-0.117*** (0.040)	-0.095* (0.051)	-0.552*** (0.038)	-0.553*** (0.036)	-0.447*** (0.056)	0.447 (0.278)	-0.273*** (0.027)	-0.057* (0.033)
Cognitivescore	1.406*** (0.099)	0.797*** (0.059)	1.977*** (0.111)	0.687*** (0.078)	1.264*** (0.067)	1.342*** (0.048)	0.391*** (0.062)	0.310 (0.400)	0.786*** (0.062)	0.700*** (0.089)
Cognitive-1980	-0.181*** (0.064)	0.004 (0.062)	-0.232*** (0.060)	0.175*** (0.052)	0.061** (0.030)	0.488*** (0.037)	0.305*** (0.065)	0.397 (0.431)	0.068*** (0.019)	0.171*** (0.038)
Cognitive-1990	0.013 (0.066)	0.158*** (0.049)	-0.320*** (0.066)	0.361*** (0.056)	0.234*** (0.032)	0.768*** (0.040)	0.214*** (0.071)	0.403 (0.418)	0.030 (0.025)	0.173*** (0.048)
Cognitive-2000	0.290*** (0.076)	0.361*** (0.063)	-0.106** (0.041)	0.611*** (0.049)	0.390*** (0.029)	0.851*** (0.038)	0.224*** (0.063)	0.109 (0.427)	-0.057** (0.022)	0.152*** (0.051)
Cognitive-2010	0.264*** (0.075)	0.495*** (0.057)	-0.159*** (0.049)	0.793*** (0.051)	0.225*** (0.027)	0.837*** (0.030)	0.219*** (0.056)	0.086 (0.393)	-0.097*** (0.030)	0.196*** (0.040)
<i>N</i>	317338	195400	105061	175128	185606	294177	215306	7068	216845	92513
<i>R</i> <sup>2</sup>	0.264	0.272	0.223	0.168	0.289	0.190	0.183	0.252	0.305	0.179

Standard errors in parenthesis are clustered by state.

Other control variables are not shown.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

corresponding dummy coefficient. The x-axis denotes these composite values for routineness, while the y-axis represents cognitiveness. Consequently, each point on the graph elucidates the combined impact of routine and cognitive factors on wage remuneration.

An examination of this graphical representation reveals two salient observations. Primarily, a consistent and substantial upward trajectory is discernible in the cognitive coefficients for female workers, albeit this trend is predominantly observable in the service, sales, and to a lesser extent, management occupations. This pattern suggests a progressive increase in the wage premium associated with

Figure 12: The Effect of Routine and Cognitive Skill Levels on Wages, 1970-2020

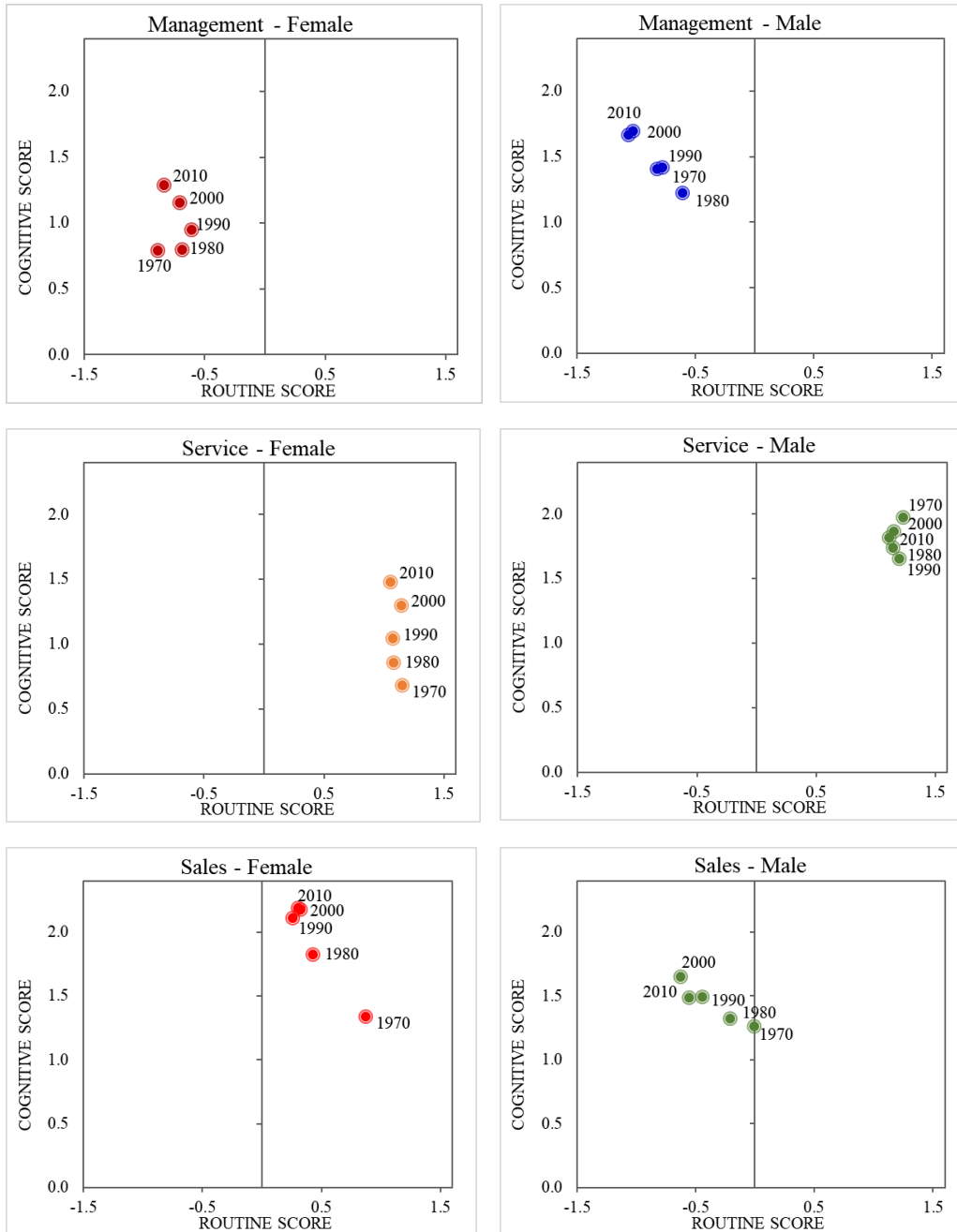
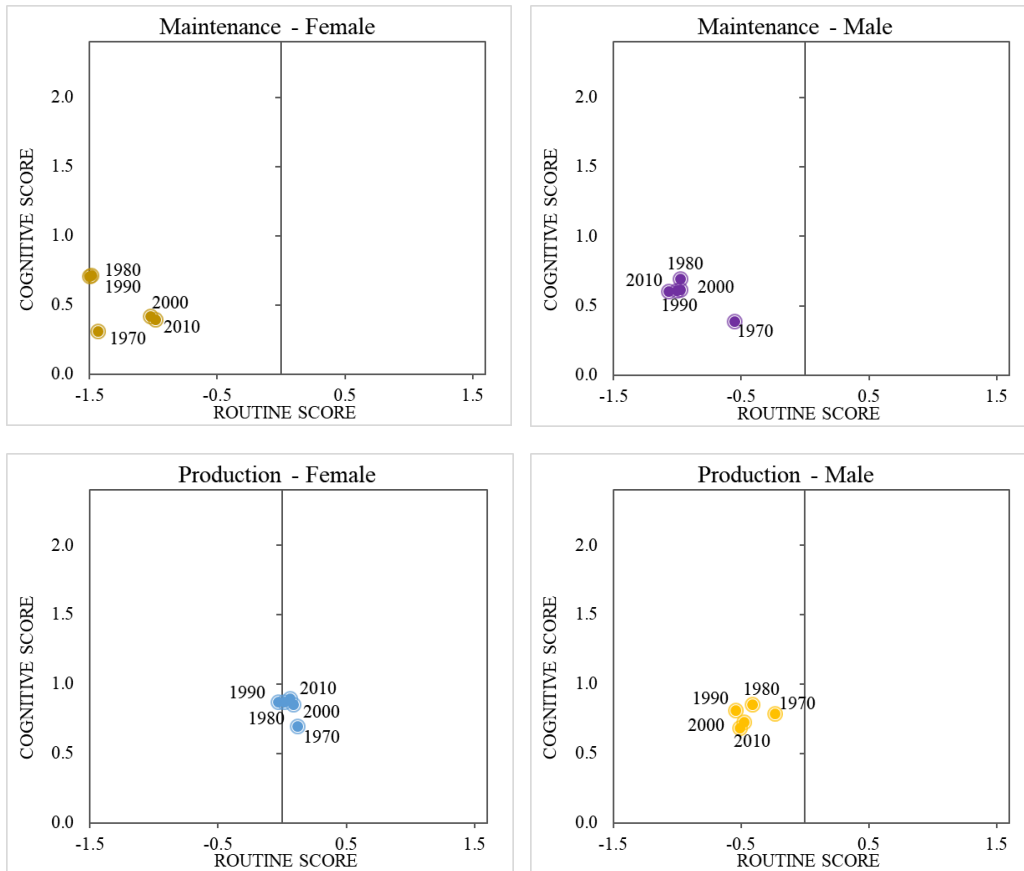


Figure 12: (Continued) The Effect of Routine and Cognitive Skill Levels on Wages, 1970-2020



cognitive tasks for women within these specific occupational domains. It is noteworthy that other occupational categories do not exhibit comparable changes, even for the female cohort.

Secondly, the routine coefficients exhibit remarkable stability across the observed temporal span. This consistency across occupations and time periods may indicate a lack of significant historical correlation between routine task intensity and wage determination. An exception to this trend is observed in the sales and management occupations. For male employees in these fields, as the RTI-LLM decreases, indicating a shift towards more non-routine tasks, there is a corresponding increase in wage compensation.

These findings carry potential implications for our understanding of labor market dynamics. The upward trend in cognitive coefficients for females may be

indicative of women overcoming historical wage disparities through increased engagement in cognitive-intensive tasks. This interpretation, however, warrants further investigation to establish causal relationships and to account for potential confounding variables. Future research could explore the underlying mechanisms driving these trends and their broader implications for labor market policies and practices.

Figures 13 and 14 supplement the aforementioned findings. These three-dimensional density plots utilize a color gradient, with yellow indicating high density. The x-axis represents skill, which, following the methodology of Autor and Dorn (2013), is proxied by wage. The y-axis denotes either RTI-LLM (Figure 13) or CTI-LLM (Figure 14). In Figure 13, the area of highest density was initially concentrated in the high-routine region. However, over time, this concentration has shifted, becoming bimodal with peaks at both high and low routine levels, with a greater emphasis on the latter. Figure 14 exhibits a similar trend: the initial concentration in the low-cognitive region has evolved into a bimodal distribution, with peaks at both high and low cognitive levels, but with a stronger emphasis on the former.

These observations align with the trends depicted in Panel (a) of Figure 4. A notable finding is that despite the shift from routine to non-routine tasks, wages have not shown a corresponding increase. In contrast, the transition from low to high cognitive tasks is associated with significant wage changes. These results corroborate the findings from the primary regression analysis, particularly as illustrated in Figure 12.

## 7. Conclusion

This paper introduces a novel approach to measuring Routine Task Intensity (RTI) and Cognitive Task Intensity (CTI) using Large Language Models (LLMs) to analyze O\*NET task descriptions at a granular, six-digit SOC level. We term these new measures Routine Task Intensity determined by LLM (RTI-LLM) and Cognitive Task Intensity determined by LLM (CTI-LLM). By leveraging the natural language understanding capabilities of LLMs to assess task routineness and cognitivity, we provide a new perspective that complements existing approaches. Our method aims to overcome some limitations of previous measures, such as the lack of capturing ‘repetitiveness’ in Autor et al. (2003) and Autor and Dorn (2013)’s approaches and the potential arbitrariness in variable selection when using O\*NET data as in Goos et al. (2009).

Figure 13: Density of Routine and Skill Levels

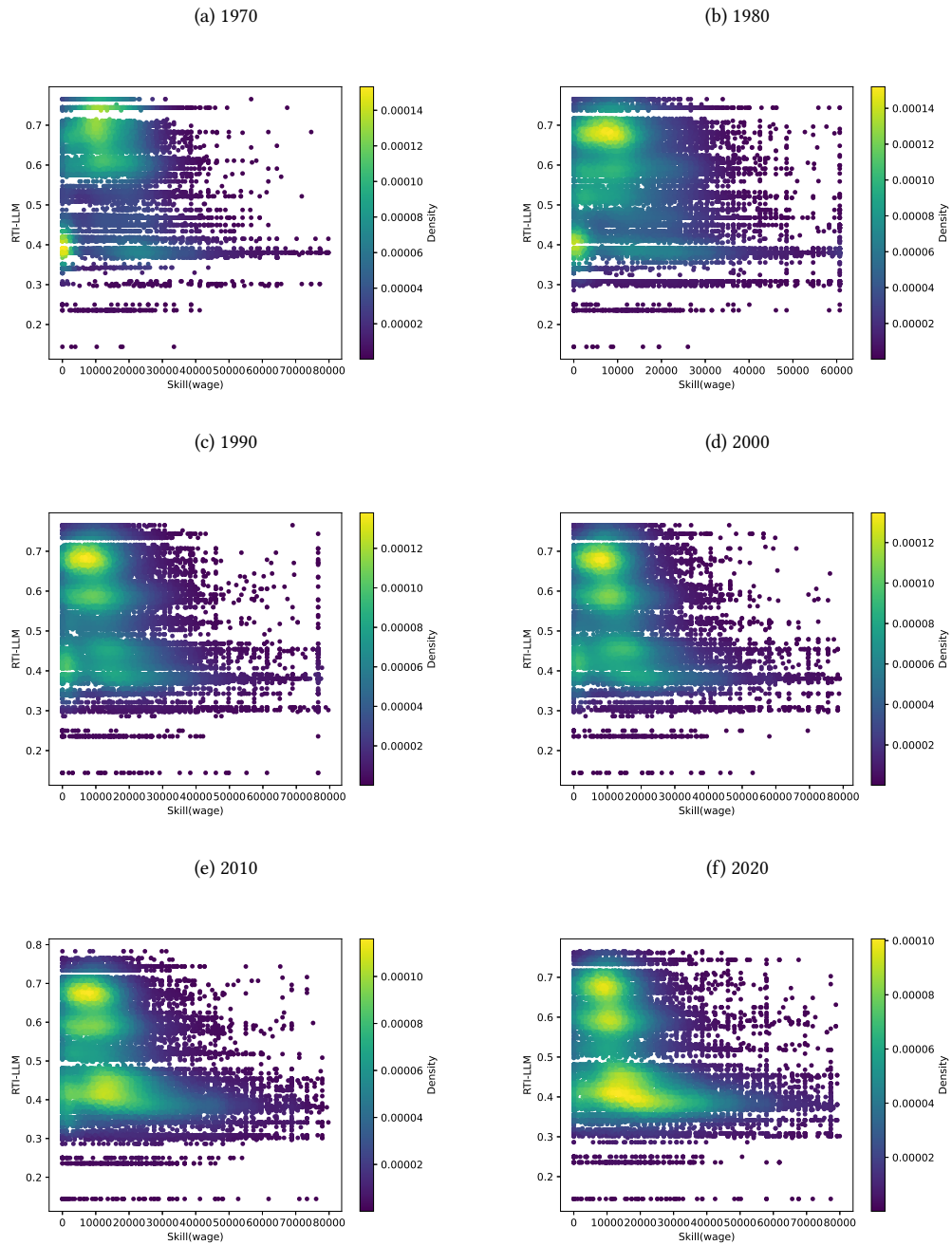
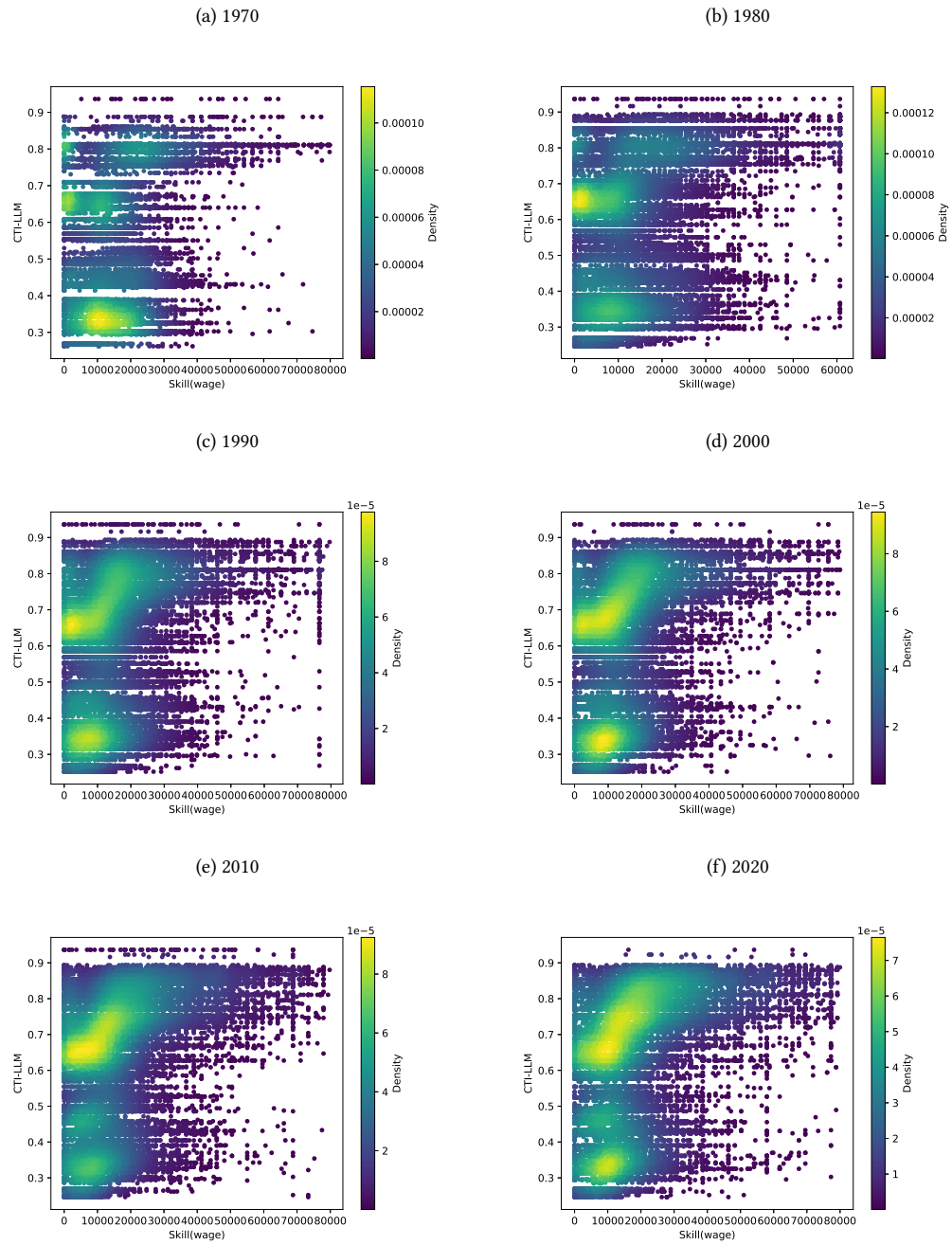


Figure 14: Density of Cognitive and Skill Levels



A key strength of this study is the application of RTI-LLM and CTI-LLM scoring at the six-digit SOC level. This granularity enables detailed analysis of compositional changes within broad occupational categories, revealing specific dynamics driving employment trends. For example, our disaggregated analysis of service occupations revealed that food preparation, serving, cleaning, and maintenance were key drivers of the decline in routine manual employment, while food preparation, serving, and personal care were principal contributors to the rise in non-routine cognitive employment.

Our longitudinal investigation yielded additional insights into labor market dynamics. A consistent diminution in the prevalence of routine occupations was observed, irrespective of cognitive dimensions, indicating a fundamental transformation in the employment landscape. While both the ‘service’ and ‘sales’ categories exhibited pronounced fluctuations, it is worth noting that [Autor and Dorn \(2013\)](#) primarily focused on service occupations in their analysis of labor market polarization. Our findings, however, suggest that a broader perspective encompassing multiple sectors may offer additional insights into this phenomenon.

Our analysis reveals that the employment magnitude within the sales occupation is commensurate with that of the service occupation, underscoring its significant presence in the labor market. Moreover, we observed substantial shifts in the routineness and cognitive demands within sales occupations. While existing literature has provided valuable insights into various occupational trends, there appears to be an opportunity for further exploration of the sales occupation and its role in labor market dynamics. In contrast to the service occupation, the sales domain exhibits distinct patterns of change, characterized by a decline in routine-cognitive tasks concurrent with an increase in non-routine-cognitive activities. We posit that this transformation within sales is a primary contributor to the consistent decrease in routine-cognitive tasks observed in ‘Total occupation.’

Our data illustrates an inverted U-shaped distribution of prior wages for individuals transitioning into both service and sales occupations, consistent with and intensifying over time. This trend is particularly noteworthy as it extends beyond the service sector, which has been the traditional focus of job polarization studies. The observation of this pattern in sales occupations as well provides stronger support for the job polarization hypothesis, suggesting a broader migration of middle-skilled workers across multiple sectors. This dual-sector trend indicates that the forces driving labor market polarization are more pervasive than previously thought.

Our regression analysis demonstrated a consistent and substantial upward

trajectory in cognitive coefficients for females in the service, sales, and to a lesser extent, management occupations. In contrast, routine coefficients exhibited remarkable stability. These findings highlight the increasing importance of cognitive skills, particularly for women in the workforce.

A notable deviation from this pattern is evident in the sales and management occupations. Within these domains, male employees exhibit a negative correlation between RTI-LLM scores and wage compensation. This inverse relationship suggests that as RTI-LLM scores decrease, indicating a shift towards more non-routine tasks, there is a commensurate rise in remuneration for male workers in these fields.

Meanwhile, our LLM-driven approach also has notable limitations. The primary concern lies in the reliability of LLMs output. Although this issue may diminish as LLM technology advances, it is important to acknowledge that the decision-making process is entirely delegated to the LLM. A secondary concern pertains to replicability. Due to the inherent variability in LLM outputs across iterations, the generated values, while similar, are not precisely identical, posing challenges for exact reproduction of results.

The third concern involves temporal relevance. Our study is well-suited for examining recent routineness, which has a close relationship with automation. However, the determination of routineness is based on current technological standards. Consequently, this methodology may not be appropriate for studying pre-2000s routineness patterns. This limitation highlights the need for caution when applying our measures to historical analyses and underscores the importance of considering technological context when interpreting results.

In conclusion, this research opens several avenues for future work, including further validation and refinement of the RTI-LLM and CTI-LLM measures, exploration of post-2000 trends in routine job shares, in-depth analysis of service occupation trajectories, and investigation of discrepancies between LLM-driven and traditional task intensity measures. Addressing the limitations of our approach, particularly regarding the reliability and replicability of LLM outputs, will be crucial for establishing the robustness and wider applicability of our methodology.



## **Appendix A. Appendix: Inconsistent Example for Cognition**

**Task description:** Visit site and record information about access, drainage and topography, and availability of utility services.

**OPUS Cognitive score:** 0.59

**OPUS Cognitive reasoning:** The task of visiting a site and recording information about access, drainage, topography, and utility services involves a combination of manual and cognitive elements. Manual aspects: - The task requires physical presence at the site, which involves manual activities such as walking, standing, and moving around the location. - Recording information may involve manual tasks like writing notes, taking photographs, or using measuring tools. Cognitive aspects: - Observing and assessing the site's characteristics, such as access points, drainage patterns, and topography, requires cognitive skills like perception, attention to detail, and spatial awareness. - Evaluating the availability of utility services involves cognitive processes such as understanding.

**GPT Cognitive score:** 0.73

**GPT Cognitive reasoning:** This task is primarily cognitive, but it also contains some manual elements. The process of visiting a site and recording information requires a significant level of cognitive activity. It involves perception to observe the site, reasoning to understand the significance of the observed features, and decision making to determine what information is relevant and needs to be recorded. These are all cognitive processes. Additionally, understanding the topography and availability of utility services involves pattern recognition and problem-solving, which are also cognitive tasks. However, there is also some degree of manual activity involved in this task. This could include physically navigating the site, perhaps using tools to measure or assess certain features, and manually recording the information.

## **Appendix B. Appendix: An Example of Core and Supplementary Tasks**

**SOC Title:** Chief Executives (11-1011.00)

**Description:** Determine and formulate policies and provide overall direction of companies or private and public sector organizations within guidelines set up by a board of directors or similar governing body. Plan, direct, or coordinate operational activities at the highest level of management with the help of subordinate

executives and staff managers.

**Core Tasks:**

- Direct or coordinate an organization's financial or budget activities to fund operations, maximize investments, or increase efficiency.
- Appoint department heads or managers and assign or delegate responsibilities to them.
- Analyze operations to evaluate performance of a company or its staff in meeting objectives or to determine areas of potential cost reduction, program improvement, or policy change.
- Direct, plan, or implement policies, objectives, or activities of organizations or businesses to ensure continuing operations, to maximize returns on investments, or to increase productivity.
- Prepare budgets for approval, including those for funding or implementation of programs.
- Confer with board members, organization officials, or staff members to discuss issues, coordinate activities, or resolve problems.
- Implement corrective action plans to solve organizational or departmental problems.
- Direct human resources activities, including the approval of human resource plans or activities, the selection of directors or other high-level staff, or establishment or organization of major departments.
- Establish departmental responsibilities and coordinate functions among departments and sites.
- Preside over or serve on boards of directors, management committees, or other governing boards.
- Negotiate or approve contracts or agreements with suppliers, distributors, federal or state agencies, or other organizational entities.
- Coordinate the development or implementation of budgetary control systems, recordkeeping systems, or other administrative control processes.

- Review reports submitted by staff members to recommend approval or to suggest changes.
- Deliver speeches, write articles, or present information at meetings or conventions to promote services, exchange ideas, or accomplish objectives.
- Interpret and explain policies, rules, regulations, or laws to organizations, government or corporate officials, or individuals.
- Prepare or present reports concerning activities, expenses, budgets, government statutes or rulings, or other items affecting businesses or program services.
- Review and analyze legislation, laws, or public policy and recommend changes to promote or support interests of the general population or special groups.
- Administer programs for selection of sites, construction of buildings, or provision of equipment or supplies.
- Direct or conduct studies or research on issues affecting areas of responsibility.

**Supplementary Tasks:**

- Direct or coordinate activities of businesses or departments concerned with production, pricing, sales, or distribution of products.
- Make presentations to legislative or other government committees regarding policies, programs, or budgets.
- Refer major policy matters to elected representatives for final decisions.
- Direct or coordinate activities of businesses involved with buying or selling investment products or financial services.
- Conduct or direct investigations or hearings to resolve complaints or violations of laws or testify at such hearings.
- Direct non-merchandising departments, such as advertising, purchasing, credit, or accounting.

- Prepare bylaws approved by elected officials and ensure that bylaws are enforced.
- Serve as liaisons between organizations, shareholders, and outside organizations.
- Attend and participate in meetings of municipal councils or council committees.
- Represent organizations or promote their objectives at official functions or delegate representatives to do so.
- Organize or approve promotional campaigns.
- Nominate citizens to boards or commissions.

## References

- Autor, David H., Lawrence F. Katz, and Melissa S. Kearney, *The Polarization of the U.S. Labor Market*, *American Economic Review*, vol. 96, no. 2, pp. 189–194, 2006.
- Autor, David H., Frank Levy, and Richard J. Murnane, *The Skill Content of Recent Technological Change: An Empirical Exploration*, *The Quarterly Journal of Economics*, vol. 118, no. 4, pp. 1279–1333, 2003.
- Autor, David H., and David Dorn, *The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market*, *American Economic Review*, vol. 103, no. 5, pp. 1553–1597, 2013.
- Cortes, Guido Matias, Nir Jaimovich, Christopher J. Nekarda, and Henry E. Siu, *The Micro and Macro of Disappearing Routine Jobs: A Flows Approach*, National Bureau of Economic Research, 2014.
- Cortes, Guido Matias, Nir Jaimovich, and Henry E. Siu, *Disappearing Routine Jobs: Who, How, and Why?*, *Journal of Monetary Economics*, vol. 91, pp. 69–87, 2017.
- Cortes, Guido Matias, Nir Jaimovich, Christopher J. Nekarda, and Henry E. Siu, *The Dynamics of Disappearing Routine Jobs: A Flows Approach*, *Labour Economics*, vol. 65, p. 101823, 2020.
- Fernández-Macías, Enrique, Martina Bisello, Eleonora Peruffo, and Riccardo Rinaldi, *Routinization of Work Processes, de-Routinization of Job Structures*, *Socio-Economic Review*, vol. 21, no. 3, pp. 1773–1794, 2023.
- Fernández-Macías, Enrique, and John Hurley, *Routine-Biased Technical Change and Job Polarization in Europe*, *Socio-Economic Review*, vol. 15, no. 3, pp. 563–585, 2017.
- Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren, Daniel Backman, Annie Chen, Grace Cooper, Stephanie Richards, Megan Schouweiler, and Westberry Westberry, *IPUMS CPS: Version 11.0 [Dataset]*, Minneapolis, MN: IPUMS, 2023.
- Freeman, Richard B., Ina Ganguli, and Michael J. Handel, *Within-Occupation Changes Dominate Changes in What Workers Do: A Shift-Share Decomposition, 2005–2015*, *AEA Papers and Proceedings*, vol. 110, pp. 394–399, 2020.

- Goos, Maarten, Alan Manning, and Anna Salomons, *Job Polarization in Europe*, *American Economic Review*, vol. 99, no. 2, pp. 58–63, 2009.
- Goos, Maarten, Alan Manning, and Anna Salomons, *Explaining Job Polarization: Routine-biased Technological Change and Offshoring*, *American Economic Review*, vol. 104, no. 8, pp. 2509–2526, 2014.
- Haslberger, Matthias, *Rethinking the Measurement of Occupational Task Content*, *The Economic and Labour Relations Review*, vol. 33, no. 1, pp. 178–199, 2022.
- Marcolin, Luca, Sébastien Miroudot, and Mariagrazia Squicciarini, *The Routine Content of Occupations: New Cross-Country Measures Based on PIAAC*, OECD Trade Policy Papers, No. 188, OECD Publishing, Paris, 2016.
- National Center for ONET Development, *ONET Resource Center*, 2023.
- Vom Lehn, Christian, *Labor Market Polarization, the Decline of Routine Work, and Technological Change: A Quantitative Analysis*, *Journal of Monetary Economics*, vol. 110, pp. 62–80, 2020.
- Walo, Simon, *The Link between Routine Tasks and Job Polarization: A Task Measurement Problem?*, *LABOUR*, vol. 37, no. 3, pp. 437–467, 2023.