Job Polarization: Evidence for Türkiye

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Abstract

In this article, we examine labour market polarization dynamics in Türkiye. First, we use highly refined microdata to classify tasks mainly abstract, routine and manual enabling us to conduct analysis at the occupationtask level. Second, we find evidence supporting polarization driven by technological changes (the routinization hypothesis), education and increasing female employment in both low- and high-wage occupations. Lastly, we analyse the tasks performed by workers in their respective occupations and find that the occupational assignment of tasks determines their value, suggesting the existence of a structural task context.

Keywords: routinization, tasks, computerization, gender, Türkiye.

1 Introduction

Over the past two decades, the employment landscape has been significantly reshaped in numerous economies. Supply-side factors such as an aging population, growing female labour force participation, rising educational attainment levels, and foreign worker inflows intertwine with demand-side drivers such as technological advancements and trade dynamics, fundamentally altering labour market structures.

Technology advancements impact labour demand by either replacing workers or shifting job types. The skill-biased technical change (SBTC) theory suggests that new technologies boost the productivity of skilled workers, increasing demand for skilled roles and raising job skill requirements. This explains the growing wage gap and rise in high-skilled jobs in developed countries in recent decades (e.g. Bound and Johnson 1992; Katz and Murphy 1992; Berman, Bound and Machin 1998; Machin and Van Reenen 1998; Spitz-Oener 2006; Dauth et al. 2021). However, in the 2000s, the United Kingdom and the United States saw growth in low- and high-skilled jobs but a decline in middle-skilled jobs (Autor, Katz and Kearney 2006; Goos and Manning 2007; Acemoglu and Autor 2011). This shift, known as routinization or routine-biased technical change (RBTC), was first identified by Autor, Levy and Murnane (2003). The RBTC model explains how automation of routine tasks and increased demand for abstract tasks causes a shift from middle-skilled to manual occupations, resulting in job polarization (Goos and Manning 2007).

On the supply side, female labour market participation has increased significantly. In the United States, female employment rose from 35 per cent in 1945 to 77 per cent by the end of the century. In Europe, it increased from 46.3 per cent in 1990 to 50.93 per cent in 2015. This growth is due to the expansion of the service economy for which womens skills have been found to be well suited (Goldin 2006; Galor and Weil 1996; Ngai and Petrongolo 2017) and to more women entering both lower- and higher-paying jobs. This trend reflects the expansion of the service economy, evolving job requirements and improvements in womens education and empowerment, significantly impacting future work dynamics. In addition to examining female labour force participation, several studies highlight the influence of worker age on de-routinization. For instance, Lewandowski et al. (2020) find that the transition from routine to non-routine tasks in European labour markets occurred at a significantly faster pace among workers aged 25 44 than among older workers.

Job polarization, characterized by the growing disparity between high- and low-wage jobs, has been documented in various countries. Studies by Autor, Levy and Murnane (2003), Autor and Dorn (2013), Goos, Manning and Salomons (2009) and Van Reenen (2011) attribute this phenomenon to advances in information and communications technology (ICT). Additionally, research by Blinder (2007) and Jensen and Klezer (2010) investigates immigration and offshoring as contributing factors. Within a theoretical framework, Grossman and Rossi-Hansberg (2008) develop a model of offshoring based on tradeable tasks. They identify a productivity effect resulting from task trade, which reflects a more nuanced international division of labour. This effect tends to benefit the factor of production whose tasks are more readily offshored.

These studies apply the task approach, which examines how changes in skill demands driven by technological progress or labour market transformations affect the distribution of job tasks (routine, manual and abstract). As noted by Autor and Handel (2013), this approach offers a valuable micro-foundation for understanding the link between job tasks and skills (or human capital).

Researchers have identified job polarization across various regions, with trends varying by country. Goos, Manning and Salomons (2009 and 2014) find a decline in employment in middle-wage jobs in Europe, while employment in low- and high-wage jobs has either grown or decreased modestly. Similarly, Ikenaga and Kambayashi (2016) observe an increase in the share of non-routine, high- and low-wage jobs in Japan, with a drop in middle-wage routine jobs. In the United States, Cortes (2016) note a long-term decline in wage premiums for routine jobs, coinciding with a rise in the prevalence of non-routine roles. Michaels, Natraj and Van Reenen (2014) document job polarization across several OECD countries.

While research on job polarization has focused on developed economies, fewer studies have explored this trend in developing countries. Workers in countries with higher technology adoption engage in fewer routine tasks compared with those in countries where technology adoption is lower. Hardy, Keister and Lewandowski (2016) find an increase in non-routine cognitive tasks and a decrease in manual tasks across ten Central and Eastern European countries. Helmy (2015) finds job polarization in Egypt, while Ge, Sun and Zhao (2021) reveal a 25 percentage-point decline in routine manual occupations in China from 1990 to 2015.

Signs of job polarization have also been observed in Mexico and Brazil (Maloney and Molina 2019), though wage polarization in Brazil does not appear to affect employment (Firpo et al. 2021). Fleisher et al. (2018) report a shift in China from middle-skilled jobs to unskilled jobs and self-employment, lending support to the RBTC hypothesis. Sarkar (2019) identifies a similar trend in India. However, Gasparini et al. (2021) find no clear evidence of polarization in Latin Americas six largest economies, despite the impact of automation on routine-intensive jobs. Fleisher et al. (2018) also report job redistribution in China, but no polarization in higher skill levels.

This article explores job polarization in Türkiye a topic that has been relatively under-researched. Akçomak and Gürcihan (2013) find evidence of both wage and job polarization in Türkiye from 2004 to 2010, linking wage changes to occupational shifts. Popli and Ylmaz (2017) report declining returns to routine tasks, favouring high-wage earners during the period from 2002 to 2010. Acar Erdoan and Del Carpio (2019) note a transition towards cognitive skills in higher-quality jobs, with declines in non-routine and routine manual skills. In addition, Özbay Das (2021) examines wage inequality and polarization between 2004 and 2017, concluding that there is no clear evidence of wage polarization in Türkiye.

This study contributes to the literature in four key ways. First, it deepens understanding of labour market dynamics in developing countries by examining job and wage polarization in a medium-sized economy undergoing transformation, exploring whether its job polarization trajectory differs from that of developed countries. Second, it uses refined microdata to analyse occupational tasks, focusing on abstract, routine and manual tasks, rather than the sector-level data commonly used in the existing literature (e.g. Kzlrmak 2005; Erlat and Erlat 2006; Meschi, Taymaz and Vivarelli 2011). The analysis draws on individual-level data from the Household Labour Force Survey (HLFS) conducted by the Turkish Statistical Institute (TurkStat), and assesses task content using two sources: the Occupational Information Network (O*NET), developed and maintained by the US Department of Labor, and the Programme for the International Assessment of Adult Competencies (PIAAC) of the Organisation for Economic Co-operation and Development (OECD). While O*NET provides valuable task-level information for US occupations, its use assumes uniformity in task content across countries, which may not hold in less developed economies where labour productivity, technology and skills vary significantly (Lewandowski et al. 2022; De La Rica, Gortazar and Lewandowski 2020). To address his limitation, we use country-specific occupational data for task content measures.

Third, we analyse how worker tasks are shaped by human capital, demographic characteristics and job-specific technical demands, using PIAAC microdata from a 2015 survey of approximately 5,000 individuals in Türkiye. These data provide insights into worker characteristics, such as computer experience and parental educational attainment, enhancing our task analysis and allowing us to examine the link between computer use and employment structure (Autor, Katz and Kearney 2006; Acemoglu and Autor 2011; Goos and Manning 2007; Autor and Dorn 2013). Echoing Almeida, Corseuil and Poole (2017) and Hjort and Poulsen (2019), our study is the first to connect technological advancement with job polarization in Türkiye using extensive microdata. It finds that occupational assignment plays a significant role in determining task value. Reijnders and de Vries (2018) similarly identify technological change as one of the primary drivers of employment shifts in advanced and emerging countries, including Türkiye, between 1999 and 2007, despite a decline in non-routine jobs in Türkiye due to the relocation of tasks through offshoring. Our data on technology adoption in Türkiye indicate that this effect has continued in subsequent years.

Lastly, we expand our focus to include supply factors contributing to polarization, such as womens labour market participation, education levels, and sectoral shifts, emphasizing the link between structural change and occupational structure. The existing literature suggests that economic mechanisms integrate specific preferences with technological progress (Boppart 2014; Ngai and Pissarides 2007; Acemoglu and Guerrieri 2008).

Our study shows evidence of job polarization in Türkiye from 2012 to 2022, reflected in a U-shaped wage distribution. This pattern indicates rising employment shares in both low- and high-skilled jobs, accompanied by a decline in middle-skilled jobs. Middle-wage positions were either redistributed to the extremes or filled by new labour market entrants. During this period, Türkiye experienced two crises: the 2018 economic crisis and the 2020 pandemic. Both events caused a sharp rise in unemployment but were followed by a swift recovery without fundamental labour market changes. This suggests that other structural factors, beyond these short-term disruptions, played a more significant role in shaping Türkiyes labour market.

Regression results from the PIAAC survey indicate that ICT particularly computer experience is positively associated with abstract task scores but negatively correlated with routine and manual task scores. This suggests that computerization in Türkiyes labour market may increase the demand for abstract tasks while decreasing it for routine tasks, signalling a trend toward routinization. Similarly, Sebastian (2018) finds a negative relationship between computer use and routine tasks, and a positive correlation with abstract tasks in Spain. Our findings are reinforced by a shift-share decomposition analysis, which reveals that within-industry changes implying that technology can have an impact on declining demand for routine tasks are more prevalent, while between-industry changes suggest a sectoral shift in employment. Bárány and Siegel (2018) also argue that increased relative labour productivity in manufacturing drives labour shifts toward low- and high-skilled jobs in services.

Our analysis highlights the role of women in shaping labour market dynamics in Türkiye. While technology, particularly computer use, helps explain the decline in middle-wage jobs, it does not fully account for trends at both ends of the wage distribution, where the share of female employment has increased significantly. Womens participation in interactive tasks has risen considerably, with the percentage of women in abstract jobs (e.g. professionals) rising from 8.8 per cent in 2004 to 19.2 per cent in 2022. This trend reflects a broader feminization of these roles, largely driven by rising educational attainment among women. In particular, the share of women with university education grew from 14.6 per cent in 2004 to 36.3 per cent in 2022. At the same time, womens representation in low-wage service and sales jobs rose from 7.3 per cent to 19.7 per cent.

Accordingly, job polarization in Türkiye can be partially attributed to demographic shifts, alongside technological and sectoral shifts. Our analysis of employment trends across demographic groups shows that shifts in job types are influenced by gender, age and education, as reflected in both the composition effect (changes in the size of demographic groups) and the propensity effect (changes in occupational choices).

Using PIAAC survey data, we evaluate how workers job tasks relate to their individual human capital, demographic characteristics and occupational technical requirements. Our analysis reveals that when including occupational dummies, the coefficients for education across all task categories decrease but remain statistically significant, indicating that the link between educational attainment and task types is partially dependent on occupational assignment. Notably, for manual tasks, the significant association with educational attainment disappears upon introducing occupational dummies. Additionally, we find that parental educational attainment positively correlates with abstract task scores, while negatively correlating with routine and manual task scores. This suggests an intergenerational transmission of social capital and limited occupational mobility, where individuals often occupy jobs that are in line with their parents socio-economic status.

In addition to analysing overall employment and wage polarization trends, we conducted empirical tests based on the methods of Goos and Manning (2007). Our results confirm evidence of job polarization in Türkiye between 2012 and 2022, with no indication of wage polarization, mirroring Sebastians (2018) findings for Spain. In contrast, Autor and Dorn (2013) find a strong correlation between job and wage polarization in the United States. We attribute Türkiyes divergence in this regard to the Governments active minimum wage policy, introduced in 2016. Subsequently, minimum wages approached median wage levels reaching 94 per cent of median wages in 2022 such that approximately 40 per cent of employment was made up of minimum-wage jobs. Furthermore, wage inequality declined during this period (Sefil-Tansever and Yilmaz 2024), suggesting that the minimum wage policy reduced wage sensitivity to labour market conditions.

The remainder of this article is organized as follows. Section 2 describes the data used in our analysis. Section 3 outlines preliminary trends in polarization. Section 4 examines the task content of occupations. Section 5 decomposes shifts in the industrial structure that contribute to job polarization. Section 6 analyses the demographic decomposition of tasks. Section 7 discusses the empirical results. Section 8 concludes.

2 Data

We begin by using annual microdata from the Household Labour Force Survey (HLFS), issued by the Turkish Statistical Institute (TurkStat). It provides yearly cross-sectional data covering the period from 2004 to 2022, including comprehensive information on Türkiyes labour market. Employees monthly wages and weekly working hours are used to compute a proxy of hourly wages, which is then deflated to 2010 values using the consumer price index. We select full-time and part-time employees aged 16 to 64.

When utilizing data for the entire reference period, continuity issues arise due to changes in definitions applied in Türkiye over time, in particular owing to the revision of occupation classifications in 2012. This transition involved shifting from the 1988 International Standard Classification of Occupations (ISCO88) to ISCO08. Between 2004 and 2012, there were 27 two-digit occupational categories under ISCO88, while from 2012 to 2022, ISCO08 introduced 40 categories. For 2012, data are available for both occupational coding systems. The reclassification led to a notable expansion in service jobs, with nearly 1 million additional jobs recorded. Of these, 400,000 observations were attributed to the manager category, and another 300,000 elementary occupations. However, this change cannot be traced backward or forward, as the reclassification is only vaguely defined in the report accompanying the 2012 wave of HLFS data. Accordingly, our analysis in this study focuses on the period from 2012 to 2022.

We used two data sources to determine job task content: O*NET and PIAAC. O*NET provides regularly updated information on US occupations, and many studies relying on task-based analysis have used these data. However, this approach assumes that task content is identical across countries, which may be problematic in the case of less developed countries owing to significant differences in labour productivity, technology adoption, and skills (Lewandowski et al. 2022; De La Rica, Gortazar and Lewandowski 2020). To address this, we also used the PIAAC database, including a 2015 survey of about 5,000 individuals aged 16 to 65 in selected countries, including Türkiye. The PIAAC survey offers extensive data on worker characteristics, such as computer experience and parental educational attainment, which enhance our individual-level task score estimations. It is designed to assess key information-processing skills, including literacy, numeracy and problem-solving in technology-rich environments. We estimate task measures (abstract, routine and manual) using the PIAAC survey, following the methodology of De La Rica, Gortazar and Lewandowski (2020).

Moreover, examining the level of ICT adoption is essential in order to gain insights into technological advancements within occupations. To this end, we also utilize comprehensive microdata at both the household and individual levels, sourced from the ICT Usage Survey conducted by TurkStat from 2004 to 2022.

3 Job Polarization Trends

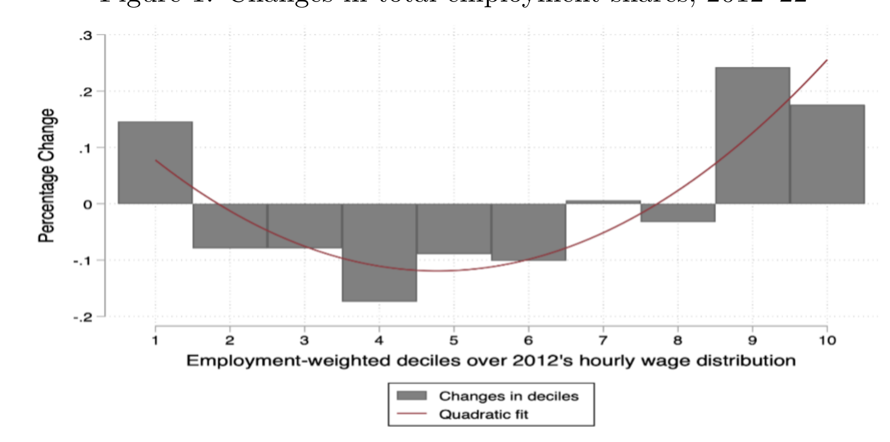
As a preliminary step to our subsequent analysis, we examine patterns of employment changes in Türkiyes labour market, applying a well-established methodology (e.g. Autor, Katz and Kearney 2006; Acemoglu and Autor 2011; Goos and Manning 2007; Autor and Dorn 2013). We thus begin by sorting two-digit occupations into deciles based on their median hourly wages.

We classify workers from lowest to highest paid, aligning them with the skill level of their occupations, from low-skilled to high-skilled. In order to avoid bias from small job categories, we sort occupations into deciles using their relative labour supplies, quantified by their contribution to total hours worked. Figure 1 shows changes in employment shares between 2012 and 2022 across the initial earnings distribution deciles. Employment shares increase in the lowest and highest deciles, while they decline in the middle (second to sixth) deciles, forming a U-shaped curve that indicates job polarization. This suggests that middle-waged jobs have either shifted to the extremes or are increasingly filled by new labour market entrants. Although the relationship between wages and skill levels is not perfect, a clear trend is evident.

Figure 2 illustrates changes in gender employment shares. For each decile, we calculate the change in employment shares attributable to men and women. Over the period, the changes in womens employment shares follow a U-shape curve. The increase at the lower end of the skill distribution is observed exclusively in the low-end services sector, which provides services that closely substitute for home production activities such as caregiving, cleaning and cooking. This suggests that women play a crucial role in generating employment polarization. At the top of the wage distribution, womens employment share also rises, owing to the increasing proportion of high-skilled women resulting from education attainment.

To explore the potential influence of technological progress on occupations, it may be useful to examine the extent of ICT adoption. Drawing on TurkStats ICT Usage Survey, we derive a proxy variable for assessing the population-wide penetration of ICT technologies. The data suggest a notable increase in ICT adoption over time, with approximately 80 per cent of the population reported as internet users by 2022. This trend could potentially reshape the task composition of occupations and influence employment dynamics. Specifically, internet usage in Türkiye appears to have grown more than sixfold between 2004 and 2022 and tripled between 2012

Figure 1: Changes in total employment shares, 2012–22



Source: Our own calculations using HLFS data.

Notes: Change numbering on Y axis to $-20, -10, 0, 10, 20$ (%). The horizontal axis represents employment-weighted deciles over the 2012 hourly wage distribution. The bars show changes in deciles, and the red line represents the quadratic fit.

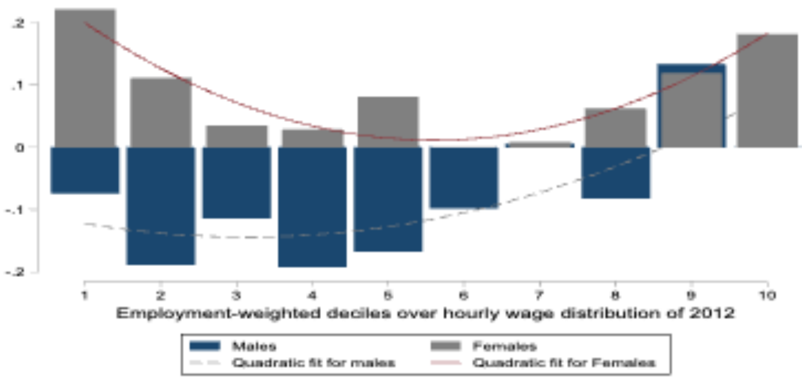
and 2022.

4 Calculating task content

To construct task indexes, we use the O*NET and PIAAC databases. These sources differ in two key ways. First, O*NET, provides task content at the occupation level, while PIAAC allows us to calculate task measures at the worker level, based on responses to individual work-related questions. Second, O*NET reflects the US labour market, whereas PIAAC includes data from various countries, including Türkiye, allowing us to capture job task differences based on local worker experiences. Autor and Handel (2013) emphasize the value of worker-level data, noting significant task variations within the same occupation, which makes PIAAC more suitable than O*NET for our analysis. In addition, Lewandowski et al. (2022) find that task measures vary across countries and are influenced by factors such as technology, skill supply and economic structure, highlighting the need to consider Türkiyes labour market specifics.

Following Acemoglu and Autor (2011), we utilize O*NET to construct standard task indices. To validate our measures, we calculate five task types (non-routine cognitive analytical, non-routine cognitive interactive, routine cognitive, routine manual and non-routine manual) using both O*NET and PIAAC and compare them with a

Figure 2: Changes in gender employment shares, 2012–22



Source: Our own calculations using HLFS data.

Notes: The horizontal axis represents employment-weighted deciles over the 2012 hourly wage distribution. The bars represent percentage changes in employment shares for males (dark blue) and females (grey). The dashed line represents the quadratic fit for males, and the solid red line represents the quadratic fit for females.

pairwise correlation table. We align O*NETs occupational coding based on the Standard Occupational Classification to ISCO using a crosswalk from Hardy et al. (2018). This crosswalk systematically links O*NET values to ISCO classifications, creating a matrix of task items for each 4-digit ISCO occupation. We then use a floor division algorithm to average these values, enabling us to merge O*NET task items with the ISCO classification employed in Türkiyes HLFS.

We construct task content measures following the taxonomy of tasks developed by Acemoglu and Autor (2011). This involves aggregating 16 task items into five standardized composite task measures. Each composite measure is calculated as the sum of the 16 pre-standardized task items, which are then standardized again to ensure that each measure has a mean of 0 and a standard deviation of 1. Standardization is essential to ensure comparability across measures, given the variation in the number of task items used to compute each composite task measure. We then construct a matrix of occupational composite task measures, where each occupation j in year t is represented by the task vector X_{jt}, with task intensity values for each of the five composite task measures. The structure is shown in the following vector:

$$X_{jt} = \left[X_{jt}^{NRCA}, X_{jt}^{NRCI}, X_{jt}^{RC}, X_{jt}^{RM}, X_{jt}^{NRM}\right] \quad (1)$$

where X_{jt}^{NRCA} denotes non-routine cognitive analytical tasks, X_{jt}^{NRCI} non-routine cognitive interpersonal tasks, X_{jt}^{RC} routine cognitive tasks, X_{jt}^{RM} routine manual tasks, and X_{jt}^{NRM} non-routine manual tasks. We also combine these five original task measures into three task aggregates: the "abstract task measure," comprising non-routine interactive and non-routine analytical tasks; the "routine task measure," comprising routine cognitive and routine manual tasks; and the "manual task measure," comprising non-routine manual tasks.

We employ a similar methodology to calculate task measures using PIAAC data, following De La Rica, Gortazar, and Lewandowski (2020), who use 12 PIAAC items to create three task categories: abstract, routine, and manual. Drawing on PIAAC-based O*NET task measures at the worker level, we average them to the occupational level for comparison with O*NET measures. We also calculate a routine task intensity (RTI) index by subtracting abstract and manual measures from the routine measure at the occupational level for both PIAAC and O*NET. The RTI measures are then normalized between 0 and 1 for comparability. The formula that we apply to construct the routine task intensities is as follows:

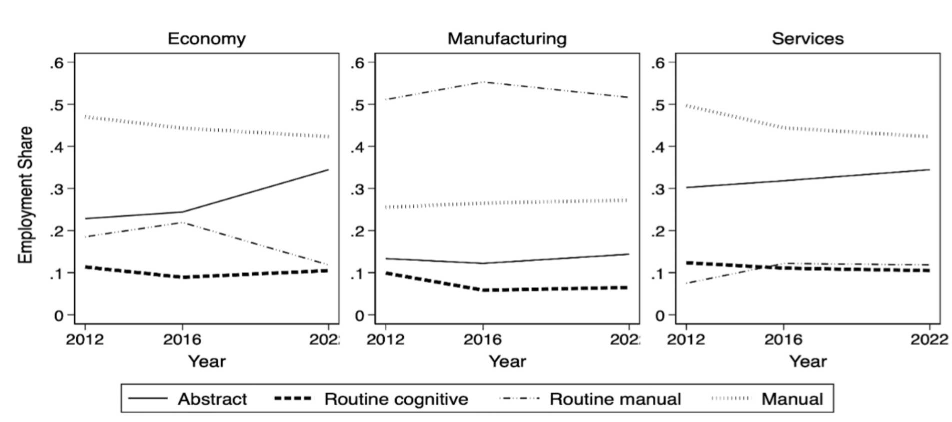
$$RTI = \ln(T^R) - \ln(T^A) - \ln(T^M) \tag{2}$$

where T^R, T^A and T^M indicate routine, abstract and manual tasks, respectively. Our summary measure RTI is positively correlated with routine tasks and negatively correlated with the abstract and manual tasks for an occupation. In other words, the positive values of RTI represent greater routine task content within an occupation.

Figure 3 shows trends in employment shares across different task types in manufacturing, services and the overall economy (including construction). We associate each occupation with its most dominant task to track these trends. The trends observed in the overall economy largely mirror those in manufacturing and services, despite shifts in task shares. Routine manual tasks are most prevalent in manufacturing, accounting for nearly 50 per cent of employment on average, compared with just 10 per cent in services. In the service sector, manual tasks dominate ranging from 60 to 50 per cent but are declining, while they account for approximately 30 per cent of tasks in manufacturing. The rise in the overall share of manual tasks can be attributed to the growing weight of the service sector in the economy. Consequently, any decrease in manual tasks in the service sector contributes to the overall downward trend in the economy.

Figure 3 also shows an increase in the share of abstract tasks in the overall economy and in both sectors. This reflects rising employment in the service sector, which relies heavily on interactive tasks a component of abstract tasks that includes both interpersonal and analytical elements. Additionally, there is a shift of approximately 68 percentage points in employment from manual to abstract tasks, while routine cognitive tasks remain relatively stable and routine manual tasks decline from 2016

Figure 3: Employment changes by task and sector, 2012–22 (percentages)



Source: Our own calculations using HLFS, O*NET and PIAAC data.

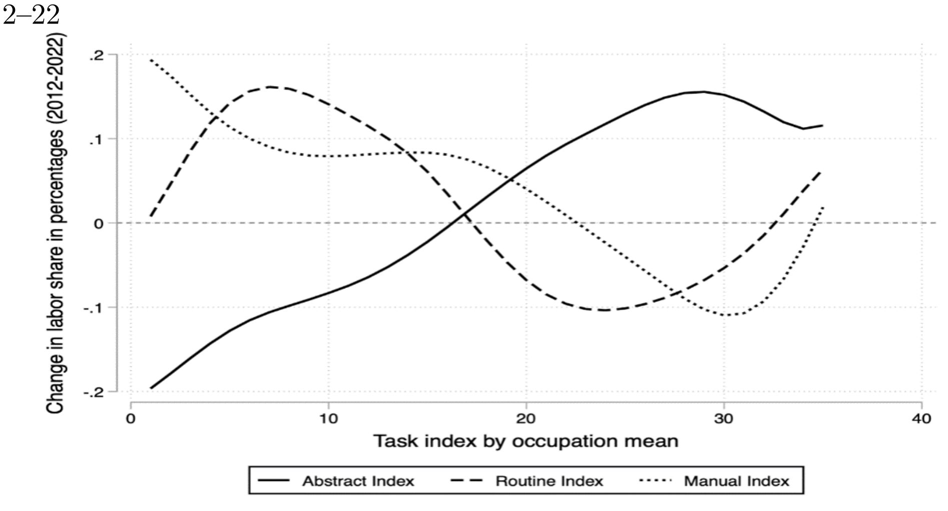
Notes: The figure displays the evolution of employment shares for three sectors: Economy (total), Manufacturing, and Services. Employment shares are calculated for four task categories: Abstract (solid line), Routine cognitive (heavy dashed line), Routine manual (dash-dot line), and Manual (dotted line). The horizontal axis shows the years 2012, 2016, and 2022.

onward. The decline in routine cognitive tasks is minimal across both sectors, though more pronounced in manufacturing. Although the increase in abstract tasks within services appears modest, their overall share in the economy has grown more significantly. This suggests that, owing to structural change, the economy has become increasingly oriented towards, and responsive to, services. The overall pattern of rising abstract task shares and declining routine manual task shares is also observed in Fonseca, Lima and Pereira (2018) for Portugal, and more recently in Kikuchi, Fujiwara and Shirota (2024) for Japan. Both studies use a framework similar to that of figure 3 to present task shares.

We also assess changes in labour share by ranking jobs based on their task intensities, allowing us to examine shifts in employment share related to an occupations position within the rankings for abstract, routine and manual tasks. In figure 4, each occupation is ranked by its intensity in abstract, routine and manual tasks, with the horizontal axis indicating task density. We apply a locally weighted smoothing regression (bandwidth = 0.8) to identify trends in labour share relative to task intensity rankings for each task.

We find a positive association between occupations with higher abstract task intensity and labour share. Conversely, occupations with higher routine task intensity are associated with a decrease in labour share. We can therefore conclude that the labour market has shifted in favour of jobs requiring high levels of abstract task in-

Figure 4: Changes in occupational employment shares for task intensity indexes, 2012–22



Source: Our own calculations using HLFS, O*NET and PIAAC data.

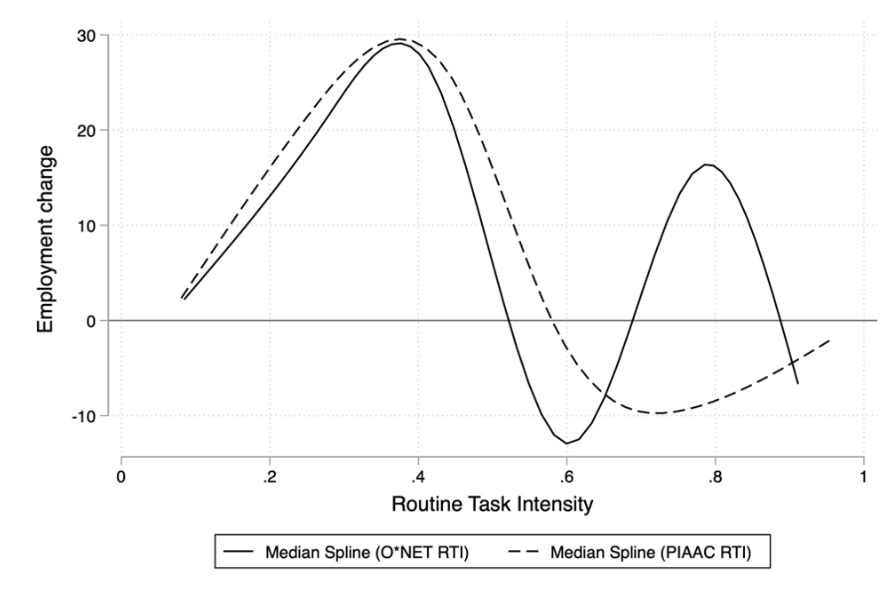
Notes: The vertical axis shows the percentage change in labor shares (2012–2022). The horizontal axis represents the task index by occupation mean. The lines represent the following categories: Abstract Index (solid line), Routine Index (dashed line), and Manual Index (dotted line).

tensity, while placing jobs with high routine task intensity at a disadvantage over the period. This provides evidence of polarization, as employment in routine-intensive occupations typically situated in the middle of the skill distribution contracts.

Figure 5 shows changes in the employment shares of occupations across the routine task intensity (RTI) index from 2012 to 2022, using both O*NET and PIAAC data. The vertical axis indicates employment changes, while the horizontal axis ranks occupations by their RTI. Median splines are used to display the overall trends, smoothing out the influence of outliers and indicating the relationship between employment share and RTI. The figure shows that employment shares increase for occupations with low RTI, but decline and eventually become negative as RTI rises. This is particularly evident in the PIAAC data, whereas the O*NET data show a temporary increase in employment shares between the sixth and the eighth deciles of the RTI distribution, before becoming negative. The PIAAC task requirements appear to better reflect Türkiyes labour market context, especially when considering other indicators of polarization.

Although we observe significant progress in educational attainment and female labour force participation over the analysis period, the broad task categories abstract, routine and manual do not fully capture these developments. While abstract

Figure 5: Changes in occupational employment shares across the routine task intensity index, 2012–22



Source: Our own calculations based on HLFS, O*NET and PIAAC data.

Notes: The vertical axis shows the percentage change in employment. The horizontal axis represents the Routine Task Intensity (RTI) index. The lines represent the median spline for O*NET RTI (solid line) and the median spline for PIAAC RTI (dashed line).

tasks often require a university-level education, where gender parity is more evident, gender disparities persist across occupations. Managerial and engineering positions remain male-dominated, whereas healthcare and education roles are predominantly female, creating gender imbalance in abstract task-intensive jobs. A better reflection of Türkiyes labour market trends requires a finer classification of task, under categories such as non-routine cognitive analytical and non-routine cognitive interactive tasks. This could help identify the means of improving gender balance within tasks.

Using the methodology followed by Lewandowski et al. (2022), we develop four distinct task measures from the PIAAC database. The non-routine cognitive analytical measure involves reading news articles, reading professional journals and problem-solving or programming. The non-routine interactive measure comprises tasks such as supervising others and delivering presentations. The routine cognitive measure involves changing the order of tasks, delivering presentations and filling out forms. Lastly, the manual task measure captures physical tasks.

Table 1 shows gender distribution changes across tasks, highlighting the role of gender in shifts in task composition. The data indicates a significant increase in

Table 1: Labour market changes by task and gender, 2012–22 (percentages)

	Non-routine cognitive analytical (%)	Non-routine cognitive interactive (%)	Routine cognitive (%)	Non-routine routine manual (%)	Unemployed or non-participation (%)	Total (%)
Women						
2012	1.13	7.08	3.43	11.79	76.57	100
2022	1.58	10.49	4.85	15.87	67.22	100
Men						
2012	3.28	14.54	19.59	34.40	28.21	100
2022	3.53	16.77	20.17	33.02	26.50	100

Notes: The sample consists of regular or casual employees who reported non-zero wages in the preceding month, excluding employers, self-employed individuals and unpaid family workers.
Source: Our own calculations based on HLFS, O*NET and PIAAC data.

womens labour force participation, from 23.43 per cent in 2012 to 32.79 per cent in 2022 a rise of 9.36 percentage points. Among men, unemployment and non-participation rates decrease slightly, from 28.21 per cent to 26.50 per cent, showing a positive, albeit smaller, trend in male labour market engagement.

In 2012, the share of women in non-routine cognitive analytical jobs stood at 1.13 per cent, rising to 1.58 per cent by 2022 an increase of 0.45 percentage points. This indicates a modest rise in the proportion of women in analytical, problem-solving roles requiring high cognitive skills. In comparison, the share of men in these occupations rises from 3.28 per cent to 3.53 per cent, indicating slower growth despite a consistently higher overall proportion.

In non-routine cognitive interactive jobs, female representation grows significantly from 7.08 per cent in 2012 to 10.49 per cent in 2022 an increase of 3.41 percentage points. This reflects greater female participation in interactive roles such as management and healthcare. The share of men in these roles increases more modestly from 14.54 per cent to 16.77 per cent a rise of 2.23 percentage points but remains higher than the share of women.

The proportion of women in routine cognitive jobs increases from 3.43 per cent to 4.85 per cent a rise of 1.42 percentage points indicating growth in female employment in routine roles requiring cognitive skills. The increase among men is again more modest from 19.59 per cent to 20.17 per cent but they nevertheless remain dominant in this category.

In non-routine manual jobs, womens representation rises considerably, from 11.79 per cent to 15.87 per cent an increase of 4.08 percentage points reflecting greater female participation in hands-on roles. Conversely, the share of men in these occupations decreases slightly, from 34.40 per cent to 33.02 per cent, although men continue to hold a larger share in this category.

5 Occupational change and task intensity over time

Job polarization can arise from both within-industry and between-industry forces. Technology adoption by firms within sectors (Goos, Manning and Salomons 2014) replaces routine tasks, reducing their demand for routine workers and polarizing sectoral workforces. The routine intensity of occupations varies across industries, such that sectoral shifts further affect aggregate occupational shares. For example, compared with services, the reliance of manufacturing on routine jobs can amplify polarization if routine-intensive sectors decline while manual- or abstract-intensive ones grow. However, if ICT or robotics drive polarization by reducing routine tasks across industries, within-industry changes should play a more dominant role in employment shifts than between-industry changes. We analyse this through industrial decomposition. To this end, we perform a shift-share decomposition to test whether industrial change could be identified as a major explanation for job polarization. The overall change of each occupation j in employment share during the period t can be expressed as:

$$\Delta E_{jt} = \kappa \Delta E_{kt} \lambda_{jk} + \kappa \Delta \lambda_{jkt} E_k \tag{3}$$

where ΔE_{jt} denotes the change in the overall share of employment in occupation j over time period t. ΔE_t^B denotes the change in the share of employment in occupation j, which is attributed to the changes in industrial composition or changes in the sectoral structure of the economy. The term ΔE_t^W presents the changes in occupation js share of employment corresponding to within-industry shifts – that is, changes in the prevalence of different occupations within sectors. In this way, we can find $\Delta E_{kt} = E_{kt_1} - E_{kt_0}$, which corresponds to the change in industry ks employment share during the period between t_0 and t_1; $\bar{E}_{kt} = (E_{kt_1} + E_{kt_0})/2$ is the average employment share of industry k over time period t; $\Delta\lambda_{jkt} = \lambda_{jkt_1} - \lambda_{jkt_0}$ is the change in the employment share of occupation j in industry k over the sample period; and $\bar{\lambda}_{jkt} = (\lambda_{jkt_1} + \lambda_{jkt_0})/2$ is the average employment share of occupation j in industry k over time t.

For estimating occupational change as defined in equation (31), we use the HLFS data, constructed based on the second-level NACE classifications, comprising 88 divisions identified by two-digit numerical codes (01 to 99). As is common practice

Table 2: Employment changes by task and occupations, 2012–22 (percentages)

	2012–22		
	Within Δ	Between Δ	Total Δ
Managers	0.69	0.14	0.82
Professionals	3.18	1.21	4.39
Technicians and associate professionals	−0.98	0.19	−0.8
Clerks (Clerical support workers)	−1.21	0.25	−0.96
Service and sales workers	3.35	0.59	3.95
Craft and related trades workers	−1.43	−1.6	−3.03
Plant and machine operators and assemblers	−2.36	−0.43	−2.79
Elementary occupations	−1.25	−0.34	−1.58

Source: Our own calculations based on HLFS, O*NET and PIAAC data.

in the literature (Fonseca, Lima and Pereira 2018), we first aggregate these divisions into 21 sections. We then further group these sections into a broader set of sectors that better suit our methodology. This approach enables us to consistently identify nine occupational categories at the one-digit level, excluding agricultural occupations. We rank occupational groups in descending order based on average wage. Table 2 summarizes the results for within- and between-industry changes in employment shares across these occupation groups over the period of analysis.

From 2012 to 2022, the share of managerial and professional , technical, and managerial occupations (ISCO levels 1 and 2) significantly increased, driven by industries relying heavily on these roles. This rise reflects greater employment intensity within these sectors, as shown in table 2. In contrast, the share of technician (ISCO level 3) and clerical support (ISCO level 4) jobs decline, largely as a result of within-sector shifts and reduced demand for routine tasks. Employment in service and sales roles (ISCO level 5), involving non-routine physical tasks, grows during this period. Meanwhile, employment in blue-collar production and operative jobs particularly craft workers (ISCO level 7) and machine operators (ISCO level 8) declines significantly. The reduction in ISCO levels 7 and 8 roles stems from shifts within industries that reduce the need for routine manual tasks. Changes in elementary occupations (ISCO level 9) also reflect broader trends towards fewer routine and more skill-intensive roles in the labour market.

These patterns highlight the impact of technological change and structural economic transformations on employment composition a relationship further explored below. Reijnders and de Vries (2018) also suggest that technological change drove employment shifts in Türkiye from 1999 to 2007, with similar trends continuing based on technology adoption data. Beyond domestic factors, international trade and global value chain integration also shape sectoral employment patterns. Dine (2019) finds that Türkiyes participation in global value chains significantly influences employment through both backward and forward linkages, with shifts in those chains affecting various sectors. He also notes that integrating service sectors into these chains tends to reduce job numbers.

Consequently, our analysis yields several robust findings regarding occupational employment trends. First, employment shifts largely occur within sectors rather than between them. This suggests that sector-wide forces such as automation, digitization and occupation-specific technological advancements are the primary drivers of labour market restructuring, overshadowing broader intersectoral movements. However, as previously noted, within-sector employment shifts may not be solely driven by domestic factors. They may also be influenced by external forces, including international trade dynamics and integration into global value chains. Second, we observe a pronounced decline in routine occupations relative to non-routine ones, reinforcing labour market polarization. This trend has eroded middle-tier jobs, exacerbating the hollowing out of employment opportunities and contributing to growing wage inequality. Third, the decline in employment in routine work is not limited to one area but spans six distinct occupational categories, pointing to a systemic, economy-wide transformation. This structural shift reflects deeper changes in production processes, organizational practices and skill demands, rather than temporary or sector-specific disruptions. Lastly, inter-industry employment changes are largely driven by a transition from manufacturing to service-sector jobs. While employment in lower-wage manufacturing roles has contracted, it has expanded in service-sector roles particularly in sectors such as retail, hospitality and healthcare. This dynamic highlights the precarious nature of low-paid work, where job availability may persist without meaningful improvements in wages or working conditions.

6 Demographic decomposition of tasks

Our analysis period highlights notable demographic changes in the labour force, characterized by three key trends: rising average education levels, increased female labour force participation potentially associated with a more balanced distribution of educational opportunities and an aging workforce. These shifts, combined with the demographic diversity observed across occupations, necessitate a detailed analysis in order to understand the underlying factors at play. The expansion of abstract and manual occupations, alongside the contraction of routine jobs, may be linked to these demographic changes, suggesting that the probability of employment in these roles is shaped by demographic characteristics. Collectively, these trends illustrate the economic dynamics that are reshaping labour market opportunities for specific segments of the workforce.

To assess the relative importance of these two forces , we conduct decompositions by dividing the sample into 24 demographic groups based on age, education and gender. Following the methodology of Cortes, Jaimovich and Siu (2017), we categorize the sample into three age groups (1529, 3044 and 4564), four education levels (primary school education and below, lower secondary schooleducation, high schoolupper secondary education, and university education), and two gender groups (women and men). In addition, we define four occupational categories based on dominant tasks: non-routine cognitive, non-routine interactive, routine cognitive, and non-routine manual, plus a category for those unemployed or not in the labour force.

We denote the share of the population in the labour market in one of these states j at time t as $\bar{\pi}_t^j$, which can be expressed as:

$$\bar{\pi}_t^j = \sum_g w_{gt} \pi_{gt}^j \tag{4}$$

where w_{gt} represents the share of the population in demographic group g at time t, and π_{gt}^j denotes the share in demographic group g in state j at time t. The change in the share of the population in state j can be decomposed using the following set of equations:

$$\bar{\pi}_1^j - \bar{\pi}_0^j = \sum_g w_{g1} \pi_{g1}^j - \sum_g w_{g0} \pi_{g0}^j \tag{5}$$

Further decomposing equation (5) yields:

$$\bar{\pi}_1^j - \bar{\pi}_0^j = \sum_g \Delta w_g \pi_{g0}^j + \sum_g w_{g0} \Delta \pi_g^j + \sum_g \Delta w_g \Delta \pi_g^j \tag{6}$$

The first term, $\sum_g \Delta w_g \pi_{g0}^j$, represents the group size or composition effect. It captures the impact of changes in the population shares of demographic groups over time, while holding the demographic structure of state j constant at the benchmark level. The second term, $\sum_g w_{g0} \Delta \pi_g^j$, is the propensity effect, capturing the changes in the share of individuals within groups in state j. The last term, $\sum_g \Delta w_g \Delta \pi_g^j$, is the interaction effect, included to capture co-movement of demographic and propensity change.

The composition effect refers to how changes in the demographic makeup of the population influence employment trends, specifically examining how shifts in age, education levels and gender groups affect the distribution of employment across

Table 3: Decompositions based on age–gender–education, 2012–22 (percentages)

	2012 (1)	2022 (2)	Difference Total (3)	Composition (4)	Propensity (5)	Interaction (6)
NRCA (%)	2.2	2.5	0.3	1.0	−0.5	−0.2
NRCI (%)	10.7	13.6	2.9	4.5	−1.1	−0.6
RC (%)	11.3	12.4	1.1	0.5	0.3	0.2
NRM (%)	22.8	24.3	1.5	−3.3	4.2	0.6
Not working (%)	53.0	47.1	−5.8	−2.8	−2.9	−0.1

Notes: Compositions of the population across occupational groups and those not working, while excluding observations where school attendance was reported. NRCA = non-routine cognitive analytical; NRCI = non-routine cognitive interactive; RC = routine cognitive; RM = routine manual; NRM = non-routine manual.
Source: Our own calculations based on HLFS, O*NET and PIAAC data.

occupations. In contrast, the propensity effect considers how the likelihood of individuals within specific demographic groups working in certain occupations changes over time. While the composition effect focuses on the size of these groups, the propensity effect looks at changes in their occupational preferences. It is measured by keeping the population shares for all demographic groups constant at a benchmark level while allowing group-specific propensities to change.

Table 3 presents the decomposition of employment share changes across different job categories from 2012 to 2022. The categories include non-routine cognitive analytical jobs, non-routine cognitive interactive jobs, routine cognitive jobs, non-routine manual jobs, and individuals who are not working (either unemployed or out of the labour force) between ages of 16 and 64. The first two columns in the table show employment shares across these categories in 2012 and 2022. Columns (4)(6) show the decomposition results, broken down into three effects: composition, propensity and interaction.

We find that roughly 6 per cent of the population who are either unemployed or outside the labour force in 2012 transition into paid employment over the following decade, with the share declining from 53.0 per cent in 2012 to 47.1 per cent in 2022. This growth in employment is expected to alter the composition of tasks, alongside potential shifts between jobs requiring different skill sets. The data show a notable rise in employment in non-routine cognitive interactive jobs, which increases by approximately 2.9 per cent. These roles, including management, teaching, healthcare, customer service and legal professions, typically demand higher education levels and strong interpersonal skills. A rise in non-routine interpersonal task intensities is in line with trends observed in numerous developed and developing countries, as noted by Caunedo, Keller and Shin (2023).

Employment in non-routine manual occupations shows the second-largest increase, rising by approximately 1.5 per cent. These roles involve physical tasks that are less reliant on routine, such as construction and general labour tasks. Routine cognitive occupations register a modest increase of about 1.1 per cent, while non-routine cognitive analytical roles record the smallest rise, at approximately 0.4 per cent. These trends reflect broader changes in the labour market, driven by evolving skill demands and occupational structures. Caunedo, Keller and Shin (2023) similarly find that occupational employment shares and task content jointly determine how job structures evolve across countries.

For non-routine cognitive analytical jobs, the increase is mainly driven by a positive composition effect (+1.0), indicating growth in demographic groups likely to work in these roles. However, the negative propensity (0.5) and interaction effects (0.2) lead to a slight decrease in the likelihood of employment, reducing the overall employment share. In contrast, increased employment in non-routine cognitive interactive jobs is mainly driven by a strong composition effect (+4.5), reflecting significant growth in relevant demographic groups. However, the negative propensity effect (1.1) and a slight reduction from the negative interaction effect (0.6) lower the likelihood of employment in these jobs.

As regards routine cognitive jobs, the moderate increase in employment share is due to positive composition (+0.5) and propensity effects (+0.3), indicating growth both in the relevant demographic groups and in their likelihood of employment. A small positive interaction effect (+0.2) reinforces this trend. In contrast, the rising share of non-routine manual jobs is driven by a strong positive propensity effect (+4.2), suggesting an increased likelihood of working in these roles, despite the negative composition effect (3.3), indicating a shrinking demographic for these jobs.

Table 1 provides further context for these results. It reveals that female employment was predominantly concentrated in non-routine cognitive interactive and non-routine manual occupations, expanding by roughly 3.4 per cent and 4.1 per cent, respectively collectively comprising 80 per cent of all female employment in 2022. These trends are consistent with the decomposition results, especially the positive propensity effect in non-routine manual jobs a shift driven primarily by rising female labour force participation. Table 1 also highlights a decline in the male share of non-routine manual occupations, further underscoring the pivotal role of women in driving employment growth within this sector.

The trend shown in figure 2 also supports this interpretation, indicating that female employment shares rise most markedly at both ends of the wage distribution. Non-routine cognitive interactive jobs, situated at the upper end of the wage scale, absorb many highly educated female entrants. Conversely, non-routine manual jobs concentrated at the lower end of the wage distribution and involving tasks such as cooking, caregiving, and cleaning attract a significant share of new female workers, particularly those with lower educational qualifications. This dynamic is reflected in the disproportionate increase in female employment in the bottom two deciles of the wage distribution.

Taken together, these findings highlight the dual impact of demographic change. Both non-routine cognitive interactive and non-routine manual occupations play a critical role in labour market dynamics, reflecting broader trends and underscoring the increasing influence of female labour force participation a pattern well documented in the literature. The role of gender in shaping the labour market has become an increasingly prominent focus in the literature. In this context, our analysis situates this study within a broader literature that considers factors beyond the routinization hypothesis to explain job polarization.

7 Econometric Analysis

7.1 Explaining Differences in Job Tasks

This section analyses the degree to which the tasks performed by workers within their respective jobs can be explained by factors such as their individual human capital, demographic characteristics and the technical requirements intrinsic to the job itself, using the PIAAC survey conducted in 2015. Our analytical approach is based on ordinary least squares (OLS) regressions, which are structured as follows:

$$T_{ij} = \alpha + \beta_1 C_i + \beta_2 X_i + \gamma_j + \lambda_i + \varepsilon_{ij} \tag{7}$$

where T_{ij} is individual is task scale (abstract, routine, and manual) in occupation j, derived from the PIAAC survey, which includes questions designed to identify the tasks that workers perform. The vector C_i denotes the human capital measures (education, computer experience, job experience, etc.); vector X_i denotes the demographic variables (parents educational attainment, age, gender, etc.); γ_j is a vector of two-digit occupation dummies, and λ denotes the vector of firm size (3 categories) and industry (21 categories) dummies. The reference group comprises women with lower secondary or less education, those aged 15–19, and those whose parents have not completed upper secondary school.

The OLS results in table 4 show significant associations with some of the variables. The even-numbered columns (2, 4 and 6) correspond to estimations using two-digit ISCO08 occupation dummies. When including occupation, dummies substantially

Table 4: Estimation results of task scores with individual characteristics

	Abstract		Routine		Manual	
	(1)	(2)	(3)	(4)	(5)	(6)
Human capital variables						
Education dummy (ref. lower secondary or less)						
Upper secondary	0.23***	0.13*	−0.13*	−0.036	−0.100	0.053
	(0.00)	(0.02)	(0.02)	(0.52)	(0.09)	(0.35)
Tertiary: 2–3 years	0.70***	0.50***	−0.51***	−0.30**	−0.18	0.057
	(0.00)	(0.00)	(0.00)	(0.00)	(0.06)	(0.53)
Tertiary: 4 years	1.05***	0.68***	−0.78***	−0.39***	−0.35***	−0.058
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.54)
Tertiary: Master	1.39***	0.96***	−1.10***	−0.63***	−0.58***	−0.24
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.14)
Computer experience	0.30***	0.20**	−0.40***	−0.36***	−0.20**	−0.044
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.49)
Tenure	0.018*	0.014	−0.042***	−0.038***	0.0067	0.0067
	(0.02)	(0.05)	(0.00)	(0.00)	(0.43)	(0.39)
Tenure^2	−0.035	−0.031	0.095***	0.091***	−0.036	−0.032
	(0.11)	(0.14)	(0.00)	(0.00)	(0.13)	(0.16)
Demographic variables						
Parents education (ref. neither of parents attained upper secondary)						
Secondary	−0.06	0.03	−0.04	−0.18*	−0.14	−0.07
	(0.74)	(0.58)	(0.03)	(0.07)	(0.38)	(0.46)
Tertiary	0.29**	0.24*	−0.27*	−0.23*	−0.23*	−0.23*
	(0.00)	(0.02)	(0.01)	(0.03)	(0.04)	(0.03)
Gender dummy (man = 1)	−0.12*	−0.12*	0.09	0.11*	0.12*	0.17**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)
Age (5-year intervals)	0.01	0.00	−0.01	0.00	−0.06***	−0.05**
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Constant	−0.39	−0.59*	0.73***	0.99***	−0.21	−0.68*
	(0.21)	(0.27)	(0.22)	(0.28)	(0.23)	(0.28)
Occupation dummies	No	Yes	No	Yes	No	Yes
Industry and firm size dummy	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1,691	1,691	1,692	1,692	1,694	1,694
Adjusted R^2	0.282	0.355	0.279	0.343	0.184	0.325

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent levels, respectively.
Notes: All the regressions are weighted with sampling weighted using the PIAAC dataset. Standard errors appear in parentheses.
Source: Our own calculations based on HLFS, O*NET and PIAAC data.

augment the models fit across all task categories. When the occupation dummies are included, the explanatory power increases significantly.

First, we find that the education dummies are statistically significant for most regressions, with coefficients increasing (in absolute terms) with more years spent in education. While the education dummy coefficients are positive for abstract task scores, they are negative for the other two task categories. This indicates a strong positive correlation between abstract tasks and skills acquired during formal education. Moreover, the coefficient's magnitude increases with the years spent in school. When we control for the occupation dummies, the coefficients for education dummies decrease in all the abstract and routine task categories but remain statistically significant. This suggests that the relationship between education and task categories is partly dependent on occupational assignment. In the case of manual tasks, introducing occupational dummies results in the loss of statistical significance in the association between educational attainment and manual tasks.

Having computer experience appears to be positively associated with abstract task scores and negatively related to routine and manual task scores. This may suggest a link between computerization and shifts in task composition, which could support the routinization hypothesis of polarization. Routine tasks are primarily found in middle-skilled jobs such as assembly line and clerical work, which can be automated. In contrast, low-skilled service jobs, in food service and childcare, for example, demand flexibility and interpersonal skills, making them difficult to automate. High-skilled workers, such as scientists, engage in complex problem-solving tasks that complement computer capital, unlike their low-skilled service counterparts.

The PIAAC data, covering only one year, may not provide sufficient evidence of the routinization process. However, the evidence from Türkiyes ICT use survey extensive use of ICTs since 2004 suggests that routinization has developed over time, particularly between 2012 and 2022. As previously noted, significant changes in the occupational distribution of employment during the analysis period are found to occur within industries rather than between them, indicating that technological change at the occupation level is the primary driver of overall employment shifts.

Tenure (experience), as a measure of human capital, is positively associated with abstract tasks but is more critical for routine tasks. The relationship remains significant even when accounting for occupation. Notably, the association is convex, with routine scores decreasing at lower tenure levels but increasing at higher ones. Moreover, parental educational attainment correlates positively with abstract task scores and negatively with routine and manual task scores, pointing to the intergenerational transfer of social capital. This suggests occupational immobility, as individuals tend to have jobs in a similar socio-economic status to their parents.

We find that men are less likely to use abstract task scores, contradicting the expectation that they lean towards abstract jobs. This is particularly interesting given that abstract tasks include both interactive and analytical components. While employment in jobs involving interactive tasks has increased, it has declined in analytical roles, with female participation in interactive tasks rising more rapidly, indicating a feminization trend in abstract jobs. This shift is linked to womens increasing levels of educational attainment, particularly in university education, which rose from 14.6 per cent in 2004 to 36.3 per cent in 2022. Conversely, routine and manual jobs show a positive association with being a man. Notably, we find a rise in the share of womens employment in both high- and low-skill occupations, especially in non-routine manual interpersonal tasks (e.g. service and sales, childcare), increasing from 14 per cent in 2004 to 33 per cent in 2022 and mirroring trends in abstract tasks. Thus, the polarization of employment is more pronounced among women.

7.2 Polarization tests

We also perform an empirical test to examine whether employment and wage polarization follows the polarization hypothesis observed in the previous sections. To this end, we use the job polarization test proposed by Goos and Manning (2007). This test examines the prevalence of routine tasks in middle-income jobs. As routine task demand decreases, we would expect a decline in middle-income jobs, resulting in a U-shaped pattern in the employment trend. We test this convex structure using the following specification:

$$\Delta \ln E_j = \beta_0 + \beta_1 \ln \omega_{j,t_1} + \beta_2 (\ln \omega_{j,t_1})^2 \tag{8}$$

where $\Delta \ln E_j$ is the change in the log employment share in job j between t_0 and t_1, $\ln \omega_{j,t_1}$ is the logarithm of the median wage of job j at t_1, and $(\ln \omega_{j,t_1})^2$ is the square of the initial median wage. A U-shaped relationship between employment growth and wages implies that the linear term (β_1) is negative and the quadratic term (β_2) is positive. This pattern may be indicative of polarization.

This suggests that the disappearance of middle-skill jobs will cause a decline in real wages for those jobs due to changes in demand. As a result, we would expect to see a U-shaped pattern in the change in earnings. Sebastian (2018) expands on the equation to include the relationship between wage growth and the initial level of the median wage:

$$\Delta \ln \omega_j = \beta_0 + \beta_1 \ln \omega_{j,t_1} + \beta_2 (\ln \omega_{j,t_1})^2 \tag{9}$$

where $\Delta \ln \omega_j$ is the change in the log medium wage of job j in the time period, and the other parameters are the same as in equation.

We begin by utilizing annual microdata from the HLFS dataset, which covers Türkiyes labour market from 2012 to 2022. To calculate a proxy for hourly wages, we use monthly wages and weekly work hours, deflating them to 2010 values using the consumer price index. The primary unit for employment is the labour supply weight assigned to each worker, determined by multiplying the sampling weight by the usual working hours for each observation instead of counting workers.

Table 5 presents the estimation results for equations 8 and 9. The coefficients show the expected signs, with significant negative linear terms and positive quadratic terms in employment change, consistent with job polarization trends. However, we observe no wage polarization during this period, despite job polarization in employment. This anomaly may be attributed to the active minimum wage policy

Table 5: Polarization tests for jobs and wages

	$\Delta \ln E_j$	$\Delta \ln \omega_j$
Initial log median wage (β_1)	-0.730*	-0.147
	(0.37)	(0.13)
Squared initial log median wage (β_2)	0.265*	-0.05
	(0.11)	(0.04)
Constant	10.97	3.28
	(0.29)	(0.45)
Observations	32	32
R^2	0.259	0.624
Adjusted R^2	0.208	0.598

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent levels, respectively.
Notes: All the regressions are weighted with sampling weighted. Standard errors appear in parentheses.
Source: Our own calculations using HLFS data.

implemented by the Government since 2016, which resulted in minimum wages approaching median wages (94 per cent of median wages in 2022) and minimum-wage jobs accounting for over half of employment (Sefil-Tansever and Ylmaz 2024). Consequently, wages have become less sensitive to labour market conditions owing to the administrative application of minimum wages.

8 Conclusion

This article uses refined microdata to offer new insights into job polarization in Türkiye from the early 2000s onwards. Since 2012, there has been significant growth in both high- and low-skill occupations, leading to a major reallocation of employment. High-paying abstract task jobs and low-paying manual task jobs have increased, while middle-paying routine occupations have declined. The data support the polarization hypothesis for the period from 2012 to 2022, influenced by factors such as computerization, rising education levels and increasing female labour force participation. However, since 2016, active minimum wage policies have affected the degree of wage polarization, which has been less responsive to market forces.

Using PIAAC survey data, we have examined how factors such as individual human capital, demographic characteristics, and technical job requirements explain the tasks workers perform. The education dummies are significant in most regressions, with coefficients increasing in absolute terms with more years of schooling. Furthermore, our results indicate that the relationship between education and task categories varies depending on occupational assignment. Notably, parental educational attainment is positively correlated with abstract task scores but negatively correlated with routine and manual task scores. This highlights the potential for parents to transfer social capital to their children, suggesting reduced intergenerational occupational mobility.

While our analysis has focused on the primary drivers of occupational trends, other factors such as international trade and immigration, which have grown considerably since the mid-2010s may also play a role. However, data limitations and the relatively short time span of our study have prevented a comprehensive evaluation of their effects. Future research with access to more extensive data could investigate these potential contributions.

Labour market policies should prioritize lifelong learning opportunities, allowing workers to update and acquire new skills throughout their careers, facilitating their transition from routine roles to those requiring advanced capabilities. Policymakers should also promote technologies that complement human skills rather than replace them. Implementing these solutions will necessitate adjustments to current policies tailored to local needs and resources, as well as collaboration among government, industries, educational institutions, labour organizations and workers. These strategies should be customized to fit specific national and local contexts. Rather than viewing them as binary choices, they can be combined for a more comprehensive approach, effectively addressing labour market polarization and enhancing occupational mobility.

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