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THE LABOR MARKET IN TURKEY: EMPIRICAL INVESTIGATION OF POLARIZATION

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ÖZ

TÜRKİYE'DE İŞ GÜCÜ PİYASASI: POLARİZASYONUN AMPİRİK ARAŞTIRMASI

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Çalışma Ekonomisi alanında, istihdamdaki değişimlerin zaman içindeki yapısını inceleyen bir literatür giderek büyüyor. Arz yönlü bakış açısı, iş gücünün yaşlanması, kadınların iş gücüne artan katılım oranı ve eğitimde geçirilen sürenin artmasına bağlı açıklamaları önemli buluyor. Talep yönlü perspektif ise teknolojik ilerleme ve küresel ticaretin genişlemesini temel alıyor. 2000'li yılların başlarında, istihdamdaki değişimin genel özelliklerini tanımlamak için medyan ücret ile belirlenen yetenek dağılımının kuyruklarında belirgin istihdam artışına işaret eden ve "iş kutuplaşması" adı verilen bir olgu ortaya çıktı. Teknolojik ilerlemenin, değişen iş gücünün yapısındaki önemli etkisi üzerinde bir uzlaşı olmasına rağmen, bu etkinin dinamikleri ve arz yönlü etkilerin yüksek katkı düzeyine işaret eden çalışmalar, araştırmacıları çeşitli emek piyasalarına ait verileri analiz etmeye yöneltti ve farklı emek piyasalarından gelen kanıtların önemini artırdı. Bu çalışma, Türkiye emek piyasasına ait kanıtlarla bu alana katkı yapmayı amaçlamaktadır. Çalışmada temel veri seti olarak TÜİK tarafından sağlanan İş gücü İstatistikleri yıllık kesitler arası mikro veri setini kullanılır ve verinin getirdiği kısıtlar dahilinde çalışma periyodu 2004-2022 arası olarak belirlenmiştir. Veri seti, 2004-2012 ve 2012-2022 olmak üzere farklı özellikler gösteren iki parçaya bölünüp havuzlanmıştır. Literatürle uyumlu olarak göreve dayalı bir analizi kolaylaştırmak için yeni veri setleri oluşturmuştur. Hazırlanan veri setlerinden birisi, çalışanların işlerindeki görevleri ile ilgili bireysel değerlendirmelerini kapsarken diğerleri görevlerin zaman içinde değişen yapısını incelemeye olanak vermektedir.

İlk dönemde, beceri düzeyi (medyan ücretle temsil edilen) ile istihdam artışı arasında neredeyse pozitif doğrusal bir ilişki bulunmaktadır. Buna karşılık, önemli reel ücret artışlarının potansiyel olarak ikinci dönemde emek piyasasında piyasa güçlerinin ilişkisini etkilemesine rağmen, mesleklerin iş gücü içindeki paylarının değişimi kutuplaşma formuna daha yakın bir görüntü çiziyor. Kanıtlara göre, değişen sektörel kompozisyon, istihdam kaymalarının şekillenmesinde rol oynuyor. Elde edilen bulgular, 2004-2012 yılları arasında ücret polarizasyonu, 20012-2022 yılları arasındaki dönemde de iş polarizasyonu olduğuna işaret etmektedir. Mesleklere özgü özellikler, ilk dönemdeki ücret polarizasyonunu açıklama konusunda yeterlidir. Meslek ve işçi düzeyinde görev ölçümlerinin, ücret tahmini denklemleri için anlamlı indikatörler olduğu görülmüştür.

Anahtar Kelimeler: iş gücü dinamikleri, iş kutuplaşması, ücret kutuplaşması, ikame esnekliği, görev tabanlı analiz, emek piyasası, emek talebi, sektörel kompozisyon, yetenek Dağılımı

JEL kodları: J21, J24, J31

ABSTRACT

THE LABOR MARKET IN TURKEY: EMPRICAL INVESTIGATION OF POLARIZATION

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There is a growing body of literature in the field of labor economics dedicated to investigating the structural changes in employment over time. The supply-side perspective relies on the factors such as the aging of the labor force, increasing female participation, and other compositional changes influenced by educational upgrading. On the demand side, the interplay of technology and global trade is the fundamental explanation. In the early 2000's, a phenomenon called "job polarization" emerged, signifying the pronounced employment growth at the tails of the skill distribution to encapsulate and define the general characteristics of employment shifts. Although a consensus exists regarding the significance of technological advancement as a primary factor, its impact on labor demand has a level of complexity that attracts researchers to scrutinize it by employing datasets of various labor markets. The need for evidence coming from different labor markets is becoming critical. Thus, this study aims to contribute to the field by presenting evidence from Turkey. It does so by conducting an in-depth analysis of the dynamics within Turkey's Labor Market, utilizing the Labor Force Statistics series provided by TurkStat. The study period spans from 2004 to 2022, in which we pool 19 waves of annual cross-sectional micro datasets. The dataset is divided into two distinct parts: 2004-2012 and 2012-2022, each displaying distinct characteristics. Consistent with the literature, new datasets are generated to facilitate a task-based analysis. One dataset covers individual assessments of job tasks, coming from workers, while the other dataset incorporates a temporal dimension to comprehensively capture the evolving composition of tasks over time.

A nearly monotonic relationship between skill level (proxied by median wage) and employment growth is identified in the first period. In contrast, the evidence shows a different pattern closer to a polarized form, albeit substantial real wage increases potentially contaminate the second period data, thereby obscuring the effect of market forces. According to evidence, the changing sectoral composition plays a role in shaping employment shifts. The findings suggest that wage polarization occurred between 2004 and 2012, and further indicate job polarization in the period spanning from 2012 to 2022. Occupation-specific characteristics are sufficient to explain wage polarization in the initial period. Notably, measurements of tasks at both the occupation and worker levels serve as meaningful indicators for wage estimation equations.

Keywords: labor market dynamics, job polarization, wage polarization, elasticity of substitution, task-based analysis, labor market, labor demand, sectoral composition, skill distribution

JEL codes: J21, J24, J31

CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

TurkStat: Turkish Statistical Institute

LFS: Labor Force Survey

EULFS: European Labor Force Survey

PIAAC: Programme for the International Assessment of Adult Competencies

OLS: Ordinary Least Squares

RBTC: Routine Biased Technical Change

SBTC: Skill Biased Technical Change

TFP: Total Factor Productivity

NACE: European Classification of Economic Activities

ISCO: International Standard Classification of Occupations

1 INTRODUCTION

The impact of technological advancements on the distribution of work between capital and labor has been a subject of extensive study in the field of labor economics. The insights provided by Keynes (2010) in his work form a solid foundation for this thesis, given his significant emphasis on the issue of technological impact on the distribution of work between capital and labor. According to Keynes, technological efficiency is advancing so fast that creating new channels to absorb labor becomes problematic. In his text in 1930, Keynes mentions that technological developments in manufacturing and transport have progressed incomparably faster in the last decade and that this extraordinary technological innovation will spread to the production of agricultural products. He emphasized that fewer people will be required to produce the same output, eventually leading to *technological unemployment*. Similarly, Toffler (1970) acknowledged the adverse effects of rapid technological and social change on institutions and people in 1970 and suggested thinking harder to avoid technology's overwhelming impact.

According to Acemoglu and Restrepo (2018), the roots of the problems arising from machines replacing human labor in production processes can be traced back to the First Industrial Revolution. Developing specific policies for innovations such as Machine Learning, Robotics, and Artificial Intelligence is vital to prevent similar adverse effects. They challenged the assumption that productivity-increasing technologies automatically lead to increased labor demand by raising output per worker. In fact, the *displacement effect* can cause a decrease in demand for labor, as well as lower wages and employment rates. Moreover, the productivity improvements coming from automation may be causing a decline in the labor share of national income. Labor can derive benefits from automation through both the *productivity effect* and the *reinstatement effect*. As the cost of automated tasks decreases, the demand for labor increases for non-automated tasks due to economic growth. Automation also stimulates labor demand through increased capital accumulation and improved machine efficiency resulting from the *deepening of automation*. Additionally, the creation of new tasks further contributes to labor demand, particularly when labor possesses a comparative advantage over machines in performing these newly created tasks, which is known as the reinstatement effect

Technological progress, evidenced by the widespread use of capital goods in production, has led to a reduction in the relative prices of capital goods. The technical term for this reduction is *Capital deepening*, which refers to the increased share of capital in the production process relative to labor and output. In the context of technological advancements, de-skilling emerged in America–formerly in England–during the 19th century as the factory system replaced artisanal shops. The process gained momentum in the 1850s with the increased mechanization of factories through steam power. According to Katz and Margo (2013), the deskilling process predominantly affected middle-skilled jobs. Specifically, purposefully designed machines known as "special purpose, sequentially implemented" were introduced to replace artisans' manual tasks. As the cost of production using machines declined, the demand for low-skilled labor to operate these machines increased. This new type of work emerged from allocating tasks into small parts rather than a complete process. Assuming that the required skill level for a laborer whose duty is to perform a small set of tasks aided by machinery is lower than an artisan performing all stages of tasks to produce a handmade good, de-skilling has occurred by displacing middle-skilled jobs. Braverman (1974), suggested that the prominent management and production principles of the era can be reflected as "dissociation of the labor process from skills of the workers. The labor process is to be rendered independent of the craft, tradition, and the worker's knowledge. The conventional management approaches placed greater reliance on workers' expertise in carrying out their tasks, leading to a favorable scenario for workers. This stemmed from their ability to exert control over the amount of time allocated to specific tasks. Taylor (1911) targeted this "problem" of *asymmetric information* in a straightforward way: the managers, should know how the jobs could be performed best, and they should plan and give detailed instructions to workers on how the tasks are executed Pagano 2014. Another factor affecting the labor composition was the increasing production scales. As the primary factor behind this transformation, capital deepening is positively correlated with the scale of production, which was shown by Katz and Margo (2013). Therefore, larger establishment arose with geographically expanded markets, pushing the demand for high-skilled (while-collar) labor to perform newly emerged management tasks.

On the other hand, a growing number of researchers identified that the evolution of employment has not followed a monotonic increase in returns to skill, starting from the end of the twentieth century and after. Rather than a positive correlation between education level and real wage growth, it is the low-skill workforce that has gained a comparative advantage over the middle-skilled workforce. In other words, the employment growth has been higher in the tails of the education distribution. This phenomenon, called *job polarization*, has been observed in many developed countries and is beginning to become indisputable. However, further evidence is still needed to fully understand the impact of technology on employment, especially in developing countries.

Numerous studies have examined the consequences of the widespread use of computer technologies in the labor market. Despite persistently high levels of unemployment, periods of high economic growth have coincided with an increasing share of computer equipment in production processes (Brynjolfsson & McAfee, 2014). The decline in employment has primarily affected routine jobs that sophisticated algorithms can easily automate. The decrease in the employment share of manufacturing, which also contains many routine tasks, is due to this reason. The decline in middle skill employment is concentrated around the same periods as economic downturns (Charles, Hurst, & Notowidigdo, 2018). Even as unemployment rates start to decrease following these downturns, employment in routine task-based jobs does not rebound. Jaimovich and Siu (2020) conducted their research with a 35-year dataset for the U.S labor market, supplemented with data from other countries. Their findings indicate that labor markets undergoing industrial shifts and job polarization processes experience jobless recovery.

In the next subsection, we will delve into the related literature to provide a comprehensive understanding of the transformation observed in employment dynamics. Our aim is to rigorously scrutinize the available literature, conducting a chronological analysis to address the progressive development of theoretical frameworks together with empirical inquiries that span a wide array of labor markets. In the literature review section, we devote a subsection to discuss the literature focused on Turkey's labor market.

In the following section, we describe the data and conduct a descriptive analysis aimed at discerning prominent trends within Turkey's labor market. To achieve this, we employ data derived from the Household Labor Force Surveys (2004-2022) provided by the Turkish Statistical Institute (TurkStat). Building upon this groundwork, we proceed to create a dataset that encompasses task scores attributed to various occupations in Turkey. This proprietary dataset enables us to center our investigation around a task-based approach. In the third section, we present our empirical analysis to explain observed trends and the final section concludes.

1.1 Literature on Skill Biased Technical Change

Wage inequality in America began to increase after 1980, coinciding with the advent of microcomputers (L. F. Katz, 2000). This observation, linking time spent in education with workers' computer usage, highlights the complementary nature of computers to skills (Krueger, 1993). The subsequent rise in income inequality during the 1980s was explained, in part, by the notion that technological changes exhibit a bias towards skilled labor, despite the significant growth in the supply of high-skilled workers. Tinbergen's (1974) work, among others (Griliches, 1969; Welch, 1970), established a connection between the rising demand for skills and technological advancements. Tinbergen's framework suggested that the rate of increase in the highly educated workforce, driven by increased investment in education, was in a race against the demand for more high-skilled labor triggered by technological changes.

To thoroughly investigate the theoretical underpinnings of the skill-biased change in technology (SBTC), we should see what happens when a country faces a new technology. The conventional tool for this is the total factor productivity method (TFP), which, however, fails to account for the specific changes brought about by technology. The TFP framework assumes that the effect of technology parameters is consistent across different sectors and worker groups, disregarding variations in capital intensity between sectors, such as manufacturing and services. In the absence of a factor-bias in productivity, the growing supply of skills would only lead to a decline in the skill premium, as measured by wage levels. Hence, Hornstein, Krusell, and Violante (2005) compared TFP to a *black box* from which any result can be obtained (Bresnahan, 1999). Particularly during periods characterized by the invention of microelectronics and information communication technologies, the TFP framework falls short in explaining the differential wage growths experienced by different worker groups.

Building upon Tinbergen's (1974) perspective, the *canonical model* (Acemoglu & Autor, 2011, hereafter AA) incorporates two distinct skill groups: skilled (high-educated) and unskilled (low-educated), each performing occupations that are imperfectly substitutable. In this framework, job's are categorized as either high-skill or low-skill, while technology is considered exogenous and skill-biased. The model relies on two parameters to explain the relative wages: the relative supply of high-skilled and low-skilled workers and relative factor-augmenting technology terms of each worker group (A_H and A_L). The canonical model draws upon the elasticity of supply between high skill and low skill workers to interpret the effects of technological changes Acemoglu (2002). The total supply of both skills in the economy can be represented using the following equation:

$$L = \int_{i\in\mathcal{L}} l_i di \quad \text{and} \quad H = \int_{i\in\mathcal{H}} h_i di.$$

Aggregate economy can be formalized by a constant elasticity of substitution production function (Acemoglu & Autor, 2011):

$$Y = \left[\lambda(A_L L)^{\frac{\sigma-1}{\sigma}} + (1-\lambda)(A_H H)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

Where A_L and A_H are factor-augmenting technology terms, and $\sigma \in [0,\infty)$ is the term we use to denote the elasticity of substitution between two skill groups. The parameter for distribution between two labor groups is λ.

In this model described above, the interpretation of various types of technological changes depends heavily on the elasticity of substitution between two skill groups. If the elasticity of substitution is $\sigma > 1$, the skill groups are *gross substitutes*, if its $\sigma < 1$, they are *gross complements.* There are three cases for the elasticity of substitution parameter: (i) $\sigma \to 1$, which the production function approximates to Cobb-Douglas case (Acemoglu & Autor, 2011); (ii) $\sigma \to \infty$, when the two skill groups are perfectly substituting each other (there is only one skill and difference is in the quantities possessed by each labor group H and L), (iii) $\sigma \to 0$, when the two skill groups are Leontief, which means the output can be produced by using fixed proportions of either high or low skill. By assuming competitive labor markets, we can obtain the wage of the low skill unit by differentiating equation 1;

$$W_L = \frac{\partial Y}{\partial L} = (A_L)^{\frac{\sigma-1}{\sigma}}\left[(A_L)^{\frac{\sigma-1}{\sigma}} + (A_H)^{\frac{\sigma-1}{\sigma}}(H/L)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{2}$$

Acemoglu (2002) offers two hypotheses to answer why the inequality (returns to skills) increased after the 1970s but not before. These hypotheses are based on the pace of skill-bias driven by technical change. The first hypothesis, known as the *steady-demand hypothesis* maintains that the growth of demand for skills follows a constant pace, making the supply of skills the primary driver of the skill premium. The second hypothesis, termed the *acceleration hypothesis,* suggests that the skill-bias of technical change is not constant but instead accelerated by information technologies.

The steady-demand hypothesis was first tested by Katz and Murphy (1992) using data from US manufacturing sector between 1967 and 1987. Their investigation into wage inequality employed the supply and demand framework and revealed that the growth in the relative supply of college graduates played a substantial role in explaining wage differences. However, their results also indicated that the pattern of college premiums fluctuated throughout three decades instead of following a steady trajectory. Specifically, there was an increase in the 1960s, a decrease in the 1970s, and another increase in the 1980s. According to L. F. Katz and Murphy (1992, KM hereafter) this fluctuation could be attributed to the baby boomers' effect on the relative supply of college graduates.

Another study that examined the steady-demand hypothesis focused on the age groups with the same education level but experienced different wage growth paths (Card & Lemieux, 2001). They observed that the college premium for young workers was significantly larger than for older workers in the US and UK. Building a model that accounted for imperfect substitution among similarly educated workers in different age groups, they argued that the observed shift in college premium reflected changes in the relative supply of college-educated labor across age groups. Their results supported the notion that the rate of skill-biased technical change is constant, and the supply of different age cohorts plays a vital role in explaining the wage structure.

The acceleration hypothesis relies on observed advancements in information and communication technologies. Formulated on the fact that a more educated worker has significantly higher familiarity with computers, Krueger (1993), analyzed the computer's effects on the US economy and found that the information technologies partially explain the skill premiums of high-skill workers, given that more educated workers had significantly higher familiarity with computers. Another analysis by Autor, Katz, and Krueger (1998) examining a broader period (1940-1996), revealed an increasing demand for skills in the US economy from the 1960s to the 1970s. After the 1970s, this trend continued in the manufacturing sector, with higher returns to skills observed in industries with higher computer-per-worker ratios.

In summary, four supporting findings of SBTC are mentioned to explain the decreasing real wages of less skilled workers in the last two decades of the twentieth century (Berman, Bound, & Machin, 1998; Bound & Johnson, 1992; L. F. Katz & Murphy, 1992; Machin & Van Reenen, 1998): First, there is little evidence to support that product demand shifts drive employment shifts to skill-intensive sectors. Second, these employment shifts occur despite the increasing relative cost of skills and technical change, along with the increased skill demand, yields strong correlations in within-sector analyses. Finally, reports indicate that the nature of innovations tends to be labor-saving (Mark, 1987). Moreover, studies show that SBTC is effective in the US and pervasive in shifting demand toward more skilled workers across developed countries (Berman et al., 1998).

Berman et al. (1998) showed that, substitution towards skilled labor concentrated on the manufacturing industries simultaneously in developing countries. The industries with the most significant impact on skill upgrading within manufacturing were machinery (including computers), electrical machinery, and printing and publishing. While their evidence is mainly from manufacturing industries, they emphasize that the retail and financial services should also experience skill-upgrading since microprocessor-based information processing is effective on these industries. Levy and Murnane (1996) suggest that the outcome of increased skill demand in the financial industry was affected more by the expanded size of the industry than by the skill requirements of the work. Therefore, Skill Biased Technical Change (SBTC) is not just presenting a reasonable explanation for skill premium experienced in the following two decades after 1980 (Acemoglu, 2002), but it is also empirically valid (Autor et al., 1998; L. F. Katz & Murphy, 1992).

1.2 Literature on Job Polarization

The SBTC initially referred to a uniform shift in employment from low-skilled to high-skilled jobs. However, studies conducted in the US and UK since the early 2000s have shown a different trend: employment growth has been concentrated in both low- and high-skilled jobs. In contrast, jobs requiring middle-skilled workers have experienced a decline. Specifically, the employment share of managers, professionals, and technicians, along with personal service occupations, has increased, while jobs in manufacturing and routine office jobs have deteriorated. This pattern of job polarization was first observed in the US (Autor, Katz, & Kearney, 2006), UK (Goos & Manning, 2007), and Germany (Dustmann, Ludsteck, & Schonberg, 2009; Spitz-Oener, 2006). Goos and Manning (2007) suggest the term *job polarization* in their paper to name this phenomenon.

To demonstrate the pervasiveness of job polarization in Europe, Goos, Manning, and Salomons (2009) utilized the harmonized data set of the European Union Labor Force Survey (ELFS) and the German data set to analyze changes in occupational employment for 16[1] European countries from 1993 to 2006. They categorized occupations into three main groups based on their relative mean wages. Their results indicated that employment polarization occurred in 15 countries, with the employment shares of both the lowest-paying and highest-paying occu-

[1] Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Ireland, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden and United Kingdom

pations increasing relative to the middling occupations. The high-paying group saw a 22 percent increase, while the low-paying group experienced a 9 percent increase, and the middle-paying occupations faced a decline of 17 percent. Several prominent hypotheses have been proposed to explain job polarization:

- *Routinization:* According to Autor and others' (2003, ALM hereafter) observations, technological progress in recent decades involves the automation of routine tasks which computers can easily codify. Consequently, computer capital has a comparative advantage compared to workers in doing a well-defined set of cognitive and manual tasks, which can be completed by following explicit step-by-step rules. ALM coined the term "routine tasks" to describe the tasks for which computer capital substitutes for workers. On the other hand, computer capital complements workers in performing other activities, such as problem-solving, interpersonal and complex communication, or practice of creativity, which are classified as "non-routine" tasks. Assuming routine and non-routine tasks are imperfect substitutes; these observations imply shifts in the task composition of jobs which can be measured.

- *Globallization-Offshoring:* The rapid advancements in Information Communication Technologies (ICT) have significantly expanded the range of services subject to international trade. Consequently, numerous jobs that were non-tradable previously became tradable. The link between the offshoring of service jobs, which does not require spatial proximity, and *Baumol's disease*, which predicts increasing relative costs for the service sector–due to the little room for the application of technology-induced productivity growth–several studies (Blinder, 2007; Hijzen, 2007; Oldenski, 2014) links employment polarization with offshoring.

- *Wage inequality:* The income rise for high-skilled workers is the source of demand growth for low-skilled workers. Manning (2004) builds a model to capture the idea that personal service jobs, which are relatively less offshorable due to the requirement of physical proximity, are increasingly dependent on the presence of the rich in the local area. More-skilled workers, having high opportunity cost of time, are becoming more dependent on low-skilled service workers on time-intensive services such as cooking, cleaning, repairing, and delivery (Mazzolari & Ragusa, 2013). Another perspective is that the services supplied by low-skilled workers are becoming more subjected to *conspicuous consumption* of high-skilled workers (Veblen, 1889).

To test the routinization hypothesis, ALM utilizes the *Dictionary of Occupational Title (DOT)* data to construct a balanced panel of inputs from industry and occupational tasks spanning from 1960 to 1998. They link specific occupations to the degree of utilization of five distinct types of tasks based on how they are influenced by technology. The selection of these task types is based on how they are influenced by technology. The labels for these tasks are non-routine cognitive, non-routine interactive, non-routine manual, cognitive, and manual. ALM then constructs a simple model to predict computers' effect on industries and occupations. Their predictions suggest that routine task-intensive industries would invest more in computer capital to exploit comparative advantage of computers. Consequently, the labor demand for routine tasks declines while it increases for non-routine tasks. However, their model predicts that non-routine manual tasks are not significantly affected by technical change.

ALM offers an inspection of the task content of different occupations to understand the impacts of technological change on labor markets. In their conceptualization, a task is a unit of activity at work that produces output in the form of goods or services. Jobs consist of different sets of task intensities, and workers are assigned to jobs based on their capability of accomplishing the required tasks. This process induces competition among workers to allocate their skills to tasks, which determines the wage according to a task's price in the labor market. With the aid of microprocessors, the cost of performing a set of computational tasks declines enormously. Thus, employers are increasingly incentivized to substitute information technology for labor in tasks within the workplace. As technological change transfers specific tasks to computers from workers for whom the workplace tasks are less costly for computers, other workers benefit from the declining price of computation if their skills are suitable for tasks complemented by computers.

In their task model, ALM classifies tasks based on whether a computer can perform them. Accordingly, a task is labeled as "routine" if a machine can execute it following an explicit set of rules programmed by engineers. Tasks that are not sufficiently decomposed into basic rules, those that are only tacitly understood and not executable by machines, are considered non-routine tasks based on Polanyi's observations. Computers complement workers performing non-routine tasks that require flexibility, creativity, generalized problem-solving capabilities, and complex communication while substituting workers whose main activities consist of routine tasks, such as record-keeping, classification, and basic calculation.

Routine tasks are common in workers' jobs in the middle segment of the educational distribution. Middle-skilled jobs such as clerical work, repetitive work on assembly lines, tellers, and monitoring jobs involve routine tasks. As the ability to program these tasks improves, relative demand increases for non-routine tasks. Furthermore, ALM divide non-routine tasks into three major categories: non-routine manual, non-routine analytical, and non-routine interactive tasks.

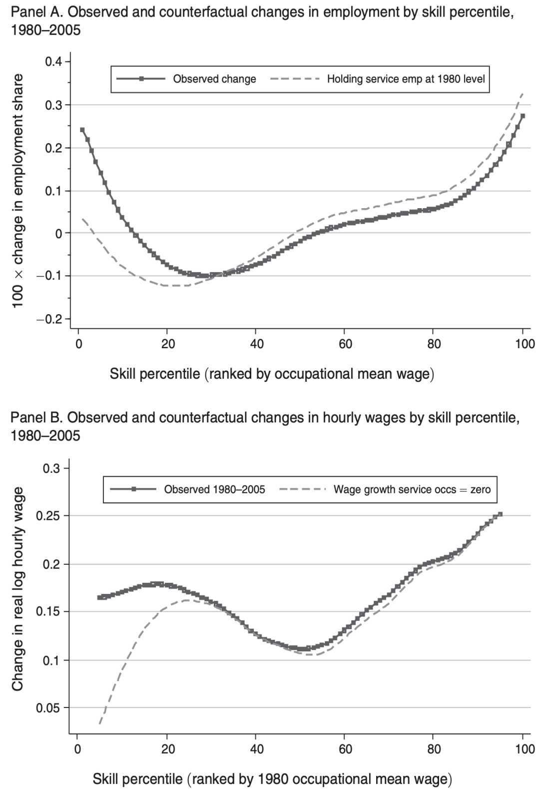
Non-routine analytical tasks are intensive in professional, managerial, technical, or creative occupations. Workers in these occupations typically have higher levels of education and possess analytical skills such as problem-solving, intuition, and persuasion. Computers complement these analytical non-routine tasks since they rely on information input from workers, and computers are designed to make information storing, categorizing, and manipulating easier.

On the other hand, workers in non-routine manual task intensive jobs are at the bottom of the education distribution. Since these tasks demand interpersonal and environmental adaptability, which belongs to a set of skills we only tacitly understand, the impact of computers on the cost of performing them is considered to be insignificant. Interestingly, due to the tacit nature of these skills, returns to education are not significant for workers in these roles.

Goos and Manning (2007) introduce Baumol's (1967) general equilibrium effect to framework the framework of ALM. Baumol (1967) argues, employment expands towards sectors of low productivity to sustain a balanced output of different products. They are merging this proposition with observation of the accumulation of non-routine jobs in both tails of the wage distribution. Based on the evidence based on the New Earnings Survey (NES) supplemented by Labour Force Survey (LFS) from the UK, Goos and Manning (2007) suggest that a polarized labor market as the outcome of technological change.

ALM focused on the growth of low-skill service jobs, which is 30 percent between 1980 and 2005 for the US. They hypothesized that the polarization is the consequence of two interacting patterns, consumers favoring variety over specialization and the secular decline in costs of routine and codifiable jobs. They showed the effect of low-skill service occupations with a simple counterfactual scenario in which service workers' employment and wage levels have remained unchanged since 1980. When they plotted the results, we can see that the upward twist in the lower tail of employment distribution was not there. The upward twist in the lower tail of employment distribution poses a simple graphical representation of why the literature switched to focus on the Routine Biased Technical Change rather than SBTC

Figure 1: Observed and Counterfactual Changes in Employment and Hourly Wages in US, 1980-2005



Source: Autor and Dorn (2013).

The figure shows a contrary pattern to the conventional narrative which argues the US Labor Market experienced a decline in low skill occupations throughout the 1980s (Autor, Katz, & Kearney, 2008). Autor and Dorn (2013) suggest the literature fails at overlooking the sectoral composition of low skill jobs and emphasize that the service jobs and non-service jobs for low-skilled exhibited countervailing trends after the 1970s in US.

Michaels, Natraj, and Van Reenen (2014) test the hypothesis that ICT's effect polarizes the labor market by causing a demand growth for high-educated while decreasing growth for middle-skilled and minimally affecting low-skilled with a unique data set. Their measurement of the adaption of new technology is ICT capital divided by value added in the EUKLEMS dataset. Findings indicate that the industries witnessing rapid growth of ICT are also experiencing demand growth for high-skilled workers, which is consistent with the studies above.

Bárány and Siegel (2018) present findings contrary to the general narrative on the job polarization debate by using the US dataset between 1950 and 2007. Their paper posits 3 facts: (i) the beginning of the employment polarization reaches to the 1950s. This fact contradicts the general narrative of ICT and Robotics induced de-routinization and polarization. (ii) Polarization is prevalent across broadly defined economic sectors. (iii) Between industry shifts is an important component of occupational employment. Based on these facts they propose a different perspective highlighting the role of structural change. In particular, the reallocation of economic activities across sectors is driven by technological progress which is not simply restricted to ICT or Robotics.

A large body of literature indicates a technology-induced, demand-driven capital-skill complementarity explanation for job polarization. Salvatori (2018) stretches the technology based explanations by using a time-extended version of the dataset used in the original paper proposing a link between occupational polarization and technology (Goos & Manning, 2007). He conducted a shift-share analysis–looking at the contribution of changes in the relative sides of educational groups and distribution of employment within education groups in explaining job polarization–by pursuing a simple reasoning that if the technology is behind the change, than it affects every country and educational groups. The results show that the evolution of jobs in the UK is substantially different than what ALM documented for the US. While in the US, job growth was favoring the bottom occupations, high-skill jobs experienced more growth than the low-skill in the UK. Moreover, increased educational attainment possesses a more considerable explanatory power than the technological change for UK.

Fernández-Macías and Hurley (2016) support Salvatori's (2018) arguments with an analysis based on an increased set of countries across Europe. Study finds that there is a great variety of patterns in employment changes in European countries. Therefore, the need for accounting for different factors to explain the labor market emphasized is in the study. Supply-side factors such as increased female participation rate, migration and educational upskilling are evident. Moreover, there are institutional factors such as state's employment stock and labor market regulations. Macro-economic factors such as growth rate and business-cycle stages should also be accounted to the analysis (Fernández-Macías & Hurley, 2016).

1.3 Literature on Turkey's Labor Market

Numerous studies focused on the labor market of Turkey shedding light on wage inequality and the impact of technical change (Aksoy, 2009; Bakis & Polat, 2015; Filiztekin, 2020; Meschi, Taymaz, & Vivarelli, 2011, 2016; Popli & Yılmaz, 2016). Bakis and Polat (2015) used household labor force survey data from 2002 to 2010 to analyze the employment structure of Turkey by using a similar framework with KM. In their study, the study period is divided into 2002-2004 and 2004-2010, an from 2002 to 2004, no significant change was observed in the relative supply of high-educated workers to low-educated workers, but wages of high-educated workers decreased in comparison to those of low-educated workers. However, from 2004 to 2010, the relative supply of high-educated workers increased, and the wages of high-educated workers either remained constant or continued to rise in comparison to low-educated workers. This indicates that there are other factors excluded by the simple supply and demand framework. Thus, they switched to the framework used by DiNardo, Fortin, and Lemieux (1996) and found that increases in real minimum wage played an essential role in reducing wage gap in Turkey. The growth of real minimum wage also helps explain the dramatically increased wages of the least educated group in the data set since the minimum wages in the formal sector mostly determine their wages.

Popli and Yılmaz (2016) studied the same dataset as Bakis and Polat (2015), but they added the occupational task content (routine, service, abstract) to their analysis. Their work showed that the growing number of universities and education reform increased the supply of educated workforce which were substantially effective on the wage distribution throughout the period. Falling college premiums and experience premiums were observed and largely contributed to the decline of wage inequality.

Tansel and Bodur (2012) studied the wage inequality of males from 1994 to 2002 using TurkStat's Household Income and Consumption Expenditure Survey and Household Budget Surveys. Their empirical work is based on the estimations of Mincerian wage equations using Ordinary Least Squares and Quantile Regression. Their results show that the male wage inequality was slightly declined over the study period, while top end and bottom end of wage distribution showed contrary patterns. Education positively effects within-groups inequality while the highest level of education contributes the most to within-groups inequality, meaning that the inequality is higher among the university-graduated male workers, the decline in the inequality comes from the decreasing between-groups wage inequality. Tansel and Bodur (2012) suggest that, considering the economic policies of Turkey in the relevant era, especially trade liberalization and promotion of foreign direct investments, global skill-biased technical change may be one of the factors behind increasing within groups inequality in high-skilled workers.

Daş and Doğruel (2017), followed a very similar methodology with Tansel and Bodur (2012), but with a broader period and found that the wage dispersion increased after Tansel and Bodur's (2012) study period. They suggest that this increase could be the outcome of the decline in union membership, since the union membership dramatically decreased to 7.8% in 2011 from 32.9% in 1994.

Tamkoç and Torul (2020), used TurkStat's Household Budget Survey (HBA) and Survey of Income and Living Conditions (SILC) micro data sets, to analyze the evolution of wage, income and consumption inequalities of Turkey over the period of 2002 to 2016. They showed that, inequality in all three variables of interest declined throughout the period. They offered findings of three reasons to explain the decrease in inequalities. First, the rapid growth in the real net minimum wage which grew 119%, and average after-tax labor earnings, which grew %56 played a significant role in reducing of inequality. The effect of real minimum wage mainly comes from the portion of minimum wage earners which was above 40% on average throughout the period. The correlation coefficient of 0.54 between Gini and real minimum wage growth supports their argument. Another factor they propose is the *countercyclicality* in estimates of wage inequality. There were two hikes in the inequality over their study period and both of them coincides with the economic crises of 2001 and 2008. As a Strong negative correlation between Gini coefficient and variance of log wages and GDP growth rates also supports their argument. The last factor they offer to explain declining wage dispersion is the informal employment ratio which was halved between 2005 and 2016, according to their estimation using the social security administration variable in the data set as a proxy.

Dervişen (2011), estimated the elasticity of substitution between high-skilled and low-skilled labor using a data set from the Turkish Manufacturing Industry between 1992 -2001. Due to the limitation of the data set, the author used manufacturing workers except technical personnel and supervisors, and workers who are coded as officers under administrative workers as a low-skilled worker group. Workers chosen to represent high skill labor consist of technicians who are classified as manufacturing workers and other administrative workers. Moreover, the minimum wage is used to represent the wage level of low-skilled labor and by subtracting it from the total payments the author obtains wage level of high-skilled labor. The estimated value of elasticity of substitution for the overall manufacturing sector is found to be -3.93 while this value is higher in sectors that uses higher technology input. The elasticity estimation predicts that a 1% increase in the relative wage of skilled labor causes a 3.93% decline in demand for skilled labor.

2 DATA AND DESCRIPTIVE ANALYSIS

This section first provides a comprehensive overview of the data and methodology used in the thesis. The primary dataset used throughout the study comes from the Household Labor Force Surveys of (HLFS) TurkStat, conforming to the standards set by the International Labor Organization (2012), with specific considerations for country-specific comparability. The dataset encompasses the period from 2004 to 2022. while changes in sampling design in 2004 and substantial alterations in 2014 led to comparability concerns within the series.

The HLFS data uses a household-level yearly repeated cross-sectional survey design. Key demographic variables such as education level, monthly wage, occupation, economic sector, working hours, and years of seniority in the current job are essential for our analysis. Given that our aim is to scrutinize the structural shifts in labor force dynamics over the past two decades, all available pertinent data is valuable. Therefore, the data-cleaning approach drops the least number of observations at each step as possible.

While the dataset provides samples starting from 2000, the comparability of years prior to 2004 is compromised by substantial changes in the sampling design which forces us to focus on the period between 2004 and 2022. Moreover, it is crucial to acknowledge that substantial alterations were introduced in 2014 to ensure compliance with European Union standards and accommodate new administrative divisions as mandated by the Turkish government. These changes rendered the series incomparable with prior data due to shifts in survey design and population projections, as documented by TurkStat. While the repeated cross-sectional data structure facilitates the investigation of time-varying relationships, unity in sampling design becomes crucial. The modifications in 2014 restrict the feasibility of pooling observations from all available periods within the dataset without making necessary arrangements.

A notable transformation within the dataset is attributed to a significant change in education classification in 2014. From 2004 to 2013, education levels were characterized based on the ISCED 1997 framework. Subsequently, starting in 2013, the education classification shifted to the ISCED 2011 framework, providing more detailed delineation of the upper tiers of educational segmentation (OECD, Eurostat, & for Statistics, 2015).

In alignment with the International Labor Office's efforts to refine classifications, TurkStat undertook transitions in occupational coding systems, moving from ISCO68 to ISCO88 in 2004 and subsequently from ISCO88 to ISCO08 in 2012.

While ISCO68 and the data preceding 2004 displayed distinct structural characteristics, ISCO88 and ISCO08 are more similar regarding occupational coding.

Despite minor changes between ISCO08 and ISCO88, ILO suggested that authoritative institutes in countries should reorganize occupation codes according to their unique labor market conditions (ILO, 2012). Therefore, the major changes in occupation shares between 2011 and 2012 can be attributed to Turkey's adjustment procedure in switching ISCO classifications.[2]

The surge in service-oriented employment in 2012 amounted to approximately one million jobs. Within this increment, 400,000 originated from the managerial category, while an additional 300,000 came from elementary occupations. A more detailed analysis of the shift from managerial occupations to service jobs reveals that 68% of the shifted observations were self-employed, while 28% were employers. This pattern highlights a straightforward approach that TurkStat employed during the adoption of the new ISCO classification.

According to ILO's report (ILO, 2012) self-employed workers are only classified as managers if their task at work primarily consists of supervising staff. Otherwise, they are assigned to occupations according to their primary tasks. Therefore it is reasonable to interpret this shift as reflecting an increasing number of small firms in growing service occupations that are coded as service jobs. The sectoral composition of these jobs is strictly subjected to the wholesale and retail trade of goods.

Table 1 shows summary statistics starting from 2004 with four years intervals. To observe general trends, agricultural workers are included in the table. These observations will be excluded in the later phase, where the general trends of wage labor will be analyzed through econometric methods. The aging speed of the labor force, increasing firm sizes, and increasing service jobs can be observed from the table at first glance. Notably, the share of workers with a university degree in the workforce has tripled throughout the sample period. The difference of average educational attainment for female and male samples is plotted in Figure 2.

When comparing the years 2004 and 2022, an upward trend in the workforce's average age becomes apparent. In 2004, 18.6% of workers fell within the age bracket of 15 to 24, declining to 14% in 2022. This trend could be attributed to a growing inclination among the youth to pursue further education rather than entering the workforce early. As a result, the labor force has witnessed increased educational attainment levels, while the retirement age continues to rise.

[2] A transition matrix provided with the 2012 Labor Force Survey data package by TurkStat describes the switching process in numbers can be found in Appendix

In 2004, the proportion of females in the workforce stood at 25%, which expanded to a level of 32% in 2022. A similar progression is observed in the ratio of having social security. Despite these improvements, there remains room for enhancement, particularly concerning issues like pension entitlements and access to healthcare services. While the prevalence of precarious employment has diminished, there has been an escalation in part-time work rates, surging from 3.8% to 18%.

Consistent with other observed trends, there has been a decrease of approximately 3 years in the average experience within current jobs. Notably, a seemingly high proportion of workers, around 90%, reported their employment as permanent in 2004. However, this figure can be misleading, as the starting point for this rate began at 55% in 2008 and has exhibited a consistent upward trajectory thereafter. Moreover, the presence of unpaid family workers and self-employed individuals within the labor force experienced a decline of over 8% over the observed period. This trend was offset by the proportion of wage or salaried employees, which reached 70% by 2022.

Table 1: Summary Statistics for Demographic Variables

	2004	2008	2012	2016	2022
Education					
Below primary	8.49%	7.9%	8.2%	6.3%	4.8%
Primary	46.5%	39.4%	35.3%	30.95%	24.1%
Secondary	12.8%	15.5%	17.7%	19.3%	17.9%
High school	20.5%	22.1%	20.34%	20.6%	25.0%
University	11.6%	15.1%	18.4%	22.7%	28.2%
Age Group					
15-24	18.6%	16.9%	15.1%	15.3%	14.2%
25-34	31.9%	32.5%	31.3%	28.6%	26.4%
35-44	27.3%	27.4%	27.8%	28.7%	28.5%
45-54	15.7%	16.7%	18.0%	18.8%	20.9%
55-64	6.5%	6.5%	7.7%	8.7%	10.0%
Female	25.5%	26.4%	29.4%	30.7%	32.5%
Married	74.1%	73.4%	72.1%	70.0%	66.2%
Having social security	51.1%	57.8%	62.2%	67.9%	75.0%
Permanency of job	89.5%	55.5%	56.6%	59.9%	64.5%
Having additional job	2.1%	2.6%	3.0%	3.3%	2.6%
Part time worker ratio	3.8%	12.0%	18.5%	17.5%	18.4%
Average tenure in job	12.2	10.2	9.4	9.7	9.5
Employment Status					
Wage or salaried employee	54.6%	61.0%	62.9%	67.6%	70.5%
Employer	5.1%	5.9%	5.0%	4.6%	4.5%
Self employed	23.3%	20.4%	18.9%	16.7%	16.3%
Unpaid family worker	17.0%	12.7%	13.2%	11.2%	8.7%
Firm Size					
<10	62.6%	57.5%	56.2%	54.2%	47.1%
10 to 50	16.6%	20.2%	21.3%	19.8%	23.7%
50 or more	20.6%	22.31%	22.2%	25.8%	29.1%
Don't know but more than 10	0	0	0	0.1%	0.1%
Workplace Type					
Field, garden	31.4%	24.9%	26.2%	20.6%	16.6%
Regular	56.6%	65.7%	63.9%	69.1%	72.6%
Market place	1.1%	0.8%	0.6%	0.6%	0.6%
Mobile or irregular	9.4%	7.3%	7.0%	7.01%	5.6%
At home	1.5%	1.3%	2.2%	2.6%	4.6%
Number of observations	131,389	135,250	159,424	164,130	211,536

Notes: The table displays changes in the demographics of the employed workforce between the ages of 15 and 64 over the data period. The values in the table may not sum up to 100 due to truncation.

Table 2: Summary Statistics for Occupation Categories and Economic Sectors

	2004	2008	2012	2016	2022
Occupation					
Managers	9.2%	8.8%	7.7%	5.2%	5.5%
Professionals	6.8%	6.4%	7.9%	10.4%	12.4%
Technicians	5.6%	7.3%	6.5%	5.7%	6.6%
Clerks	5.9%	6.8%	7.2%	7.3%	7.2%
Service and sales	11.0%	12.1%	13.0%	19.0%	19.5%
Agriculture	23.3%	17.9%	18.1%	13.5%	10.4%
Craft and related trade	15.1%	14.6%	13.2%	13.8%	13.1%
Machine operators	10.6%	11.0%	10.5%	9.5%	9.9%
Elementary	12.4%	14.9%	15.8%	15.5%	15.4%
Sector					
Agriculture	27.1%	22.1%	23.1%	18.0%	14.4%
Manufacturing and mining	20.6%	21.4%	19.5%	19.8%	22.1%
Construction	5.0%	6.0%	7.0%	7.4%	6.1%
Trade and transportation	21.0%	21.3%	18.8%	18.4%	19.3%
Accommodation and food services	4.2%	4.8%	5.0%	5.5%	5.6%
Information and communication	0.8%	0.8%	0.9%	0.94%	0.9%
Finance, insurance and real estate	1.5%	1.5%	1.8%	2.0%	2.1%
Community, personal and other services	19.6%	22.0%	23.7%	27.7%	29.4%
Number of observations	131,389	135,250	159,424	164,130	211,536

Notes: The table displays changes in the demographics of the employed workforce between the ages of 15 and 64 over the data period. The values in the table may not sum up to 100 due to truncation.

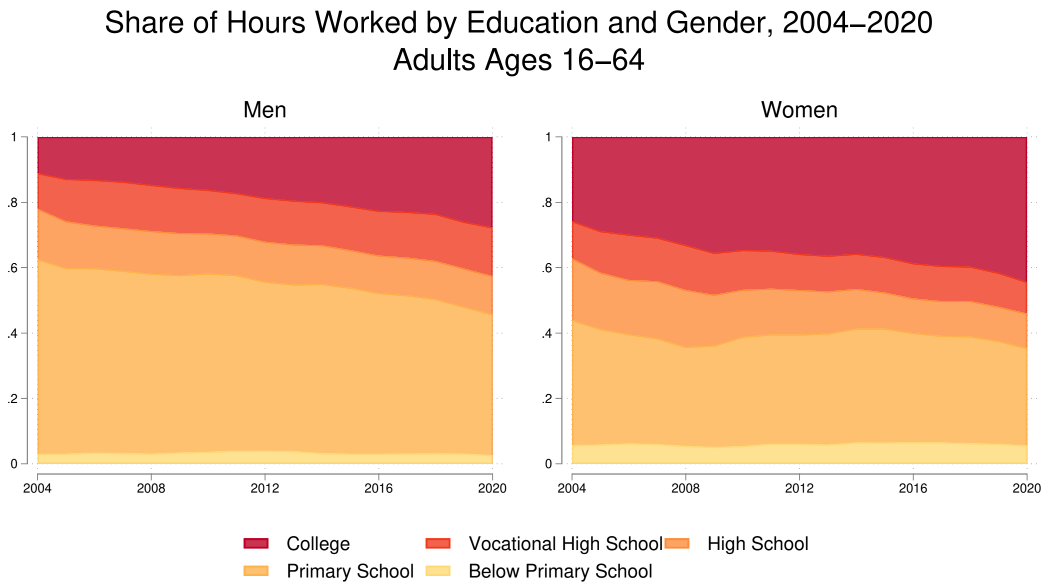
Table 2, shows substantial differences in occupations' share throughout the observed period. After a steady decline in the share of managers in the first period (2004–2012), their share dropped 2.5% in 2016 and stayed relatively stagnant after. Conversely, the proportion of professionals began ascending after 2008, displaying a relatively steady growth rate and reaching 12.4% in 2022. Meanwhile, technicians' share surged to 7.3% in 2008 and stayed more or less the same in the following period.

The workforce underwent its most significant transformation in the services and sales jobs, as well as in the proportion of agricultural workers. The proportion of agricultural workers, which once constituted nearly a quarter of the workforce, declined to 10.4% by 2022. In stark contrast, the relative size of services and sales jobs doubled, surging to 19.5% in the same year. Elementary jobs experienced a notable increase of over 3% in their share in 2012, sustained at that level after that.

Analyzing the sectoral distribution of the workforce, the community, personal, and other services sector exhibited a growth of 10% over the observed period. Conversely, a similar declining trend was observed in the sectoral share of agriculture, mirroring the pattern seen in the occupational share of agriculture. Particularly noteworthy is the continuous increase in the construction sector's share until 2016, after which a decline of 1.5% was witnessed over the subsequent 6 years.

The change in firm size parallels the change in the self-employed workforce. When considered together with the increase in the number of chain stores, the 17-year change in the Turkish workforce shows that self-employed artisans and those working in the agricultural sector with irregular income have shifted to jobs for which they receive regular wages over time.

Figure 2: Share of Hours Worked by Education and Gender



Source: Author's calculations based on HLFS, following the framework used by Autor (2019a).

There is a different structure in Figure 2. To observe labor market trends systematically, we focused solely on wage or casual employees working full-time, as hourly wage data provides a Because, we aim to observe the labor market trends in a more systematic way and hourly wage data provides a convenient tool for this purpose. In creating a consistent sample of hourly wages, we set certain restrictions, including excluding part-time workers. Following Autor (2019b), labor supply weights were calculated based on each worker's usual weekly earnings. As a result, the relationship between the total hours worked by wage earners and their education level from 2004 to 2020 has been shown. Similar to Table 1, a secular increase was observed in the share of employees with undergraduate and graduate degrees, including two-year departments. However, we encountered a limitation due to changes in education-level coding as of 2008. Before 2008, a negligible part of the workforce held master's or doctoral degrees, but after 2008, they were included in the dataset with separate coding as their share increased. To ensure comparability with the pre-2008 dataset, we considered employees with master's and doctoral degrees as university graduates.

2.1 Turkey's Labor Market Trends

In this subsection, we visualize the data set to identify labor market trends using well-studied methods in line with the literature. Firstly, we use the pioneering frame work of KM, which inspired many studies from various regions of the World, including Bakis and Polat (2015, 2021).

KM utilized a supply and demand framework to analyze changes in relative workers for different skill groups. They created two separate samples: one for measuring labor supply (count sample) and the other for measuring wages (wage sample). The wage sample aimed to maintain a relatively constant composition over time, focusing on full-time workers who are less likely to leave the labor force. On the other hand, the count sample included all workers, including part-time employees, to measure aggregate labor output.

We start by applying the supply and demand framework to Turkey to decompose the wage structure. Following KM and AA, and Bakis and Polat (2015), each wave of dataset is transformed in a way to form two samples, one of which is comprising wages and the other has the quantity of labor supplied. In order to assess the impact of labor supplied by the workers and the relative wages, the wage sample is used to determine the wage index and the count sample is used to calculate the hours of labor work for each demographic group. Demographic groups are cells that represent the labor force with the most dimensions possible. There are five education categories, which are: below 8 years of educational attainment, primary school (8 years), high school (11 years), vocational high school (12 years), and university (15+)[3]. Experience is also categorized into five groups. In similar studies, experience cells have ten years intervals (0-9, 10-19, 20, 29...). However there are several shortcomings stemming from that, such as obtaining no or too few observations for a couple of cells. To overcome this

[3]After, 2014's cross-section, the university graduates are separated into further categories. But we collapsed them into one major category of college education to maintain comparability with the previous years. More detail about the treatment on data can be found in Data Appendix.

shortcoming, the following form of categorization is used instead of ten years of equal intervals in this study: 0-5 years, 6-10 years, 11-15, 16-20, 21-48.

$$x_{new} = \begin{cases} 2, & if\ x \leqq 5 \\ 7, & if\ 6 \leqq x \leqq 10 \\ 13, & if\ 11 \leqq x \leqq 15 \\ 17, & if\ 16 \leqq x \leqq 20 \\ 30, & if\ 21 \leqq x \leqq 48 \end{cases}$$

where x_{new} stands for the new experience categories created and x is the experience levels reported by respondents.

Unlike Bakis and Polat (2015), after achieving a full working sample, log hourly and weekly wages for all observations are regressed on five education dummies, a quartic in experience, interactions of quartic in experience with education and gender dummies, and a dummy of part-time workers. After predicting log weekly and hourly wages for each series, wages are deflated by using GDP deflators. Than, we collapse the predicted log real wages into cells. Therefore, we achieve a sample of 50 observations (N = 50) consisting of education-experience-gender cells for each wave. Taking into account the assumptions of the supply and demand framework, the self employed labor and unpaid family workers are excluded. Because, aside from these two categories, our framework is based on the assumption that wage levels are signaling the comparative advantage of different endowments in the labor market.

There are N_k observations in each of the k cells representing the labor input. A wage-supply index is calculated for each cell k. In order to measure the effect of labor supply on the wage levels, the approach we follow is to create constant compositions of labor which can be followed throughout the whole period in the data set (2004 to 2020). Thus the computed wage index follows a *composition adjusted* form while the supply index helps us measure the aggregate labor supply over time.

Computation of the wage cell is given by:

$$W_k = \frac{\sum_{i=1}^{N_k} \lambda_{ik} w_{ik}}{\sum_{i=1}^{N_k} \lambda_{ik} h_{ik}}, k = 1, 2, ..., N$$

λ_{ik} stands for the sample weights, w_{ik} and h_{ik} represents real wage and working hours, respectively. We formed a matrix of *N x T,* showing hourly wage of each cell we created for demographic variables.

To create a *count sample*, the total labor supply measured by usual weekly working hours in each cell is computed using sampling weights for each observation. To obtain a relative supply index, a transformation is conducted for the sample of quantities to calculate shares of each cell by dividing the total hours worked in each cell by the total hours worked over all cells in the economy to get the employment share of each cell.

To facilitate our analysis of wage premiums for education levels, we calculate the measure called *efficiency units.* Using a *fixed wage* approach, we first computed the average relative wage for each cell. However, since the skill levels within a broad category is not homogeneously distributed, taking the average of labor supply within a category would not be an accurate measure because it does not account for the experience levels. In order to measure relative efficiencies in terms of labor for workers whose experience levels are different from each other, we need to deflate the aggregate wage of a cell with the reference wage. The relative wage of cell k, z_k, is obtained by subtracting the aggregate wage of cell k from the value of the reference wage selected for that year. The *N x T* matrix, abbreviated as *Z*, represents the average yearly wages across all demographic groups. Our *efficiency units* are the mean values of these relative wages, *Z* (an N-element column vector), over the years.[4] After creating a matrix of efficiency units, we use them to create aggregate supply indexes. First, the product of efficiency units with labor supply of the cell is computed for males and females. Than the fixed wage of the same cell is used to get the efficient labor supply of cell k ($Ek = h_k z_k$). We next create aggregate supply indexes (again in efficiency units) for further aggregate groups using these efficiency units. The total supply of efficient labor is then calculated by adding up all groups, resulting in Z0H (a T-element row vector). We obtain E, a *N x T* matrix made up of relative supplies (measured in efficiency units) of all demographic groups for each year, by deflating the efficient labor supply of each cell by the corresponding total efficient labor supply. Finally, we obtain efficient labor supply indices for these broad categories by summing over the sub-cells constituting them (for instance, skilled/unskilled). (Autor et al., 2008)

The wage indexes for broad categories, such as college graduates, are calculated using a f*ixed-weight* methodology. The aggregate wage for each category, denoted as *L* (an *N*-element column vector), is computed as the raw employment share

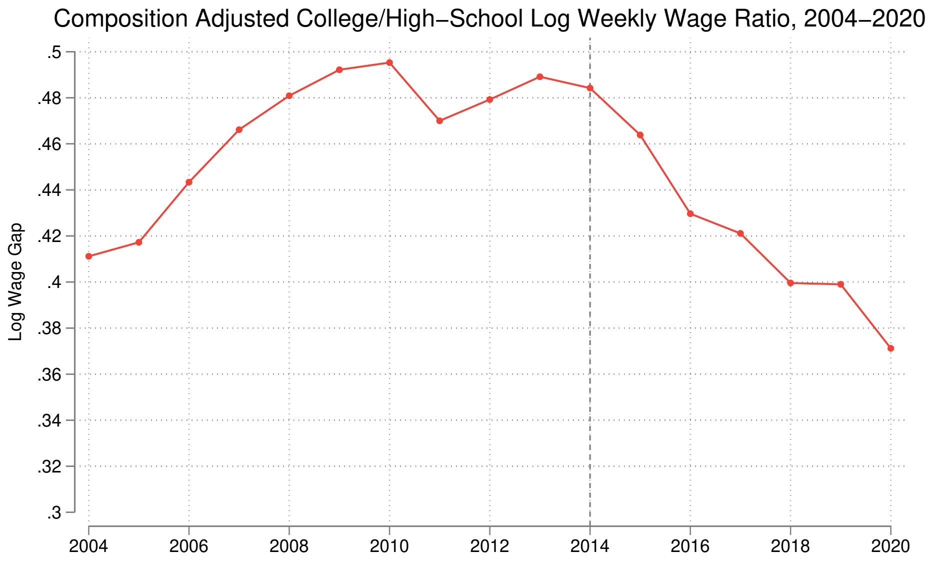
[4] In this case, we created two broad categories to see college premium: college graduates and non-college graduates. The reference wage is set to the max wage of a male with high school diploma and ten years of experience.

weighted by arithmetic means. This approach allows us to control for factors affecting the wage level in our category of interest. These aggregates are referred to as These aggregates are known as *composition adjusted* or composition constant aggregates, as they maintain the composition of major education categories over time, thus controlling for compositional changes. By making this adjustment, we ensure that shifts do not influence the estimated college premium in other controlled factors, such as gender composition, level of experience, or level of educational attainment within the categories of college graduates and non-college graduates.

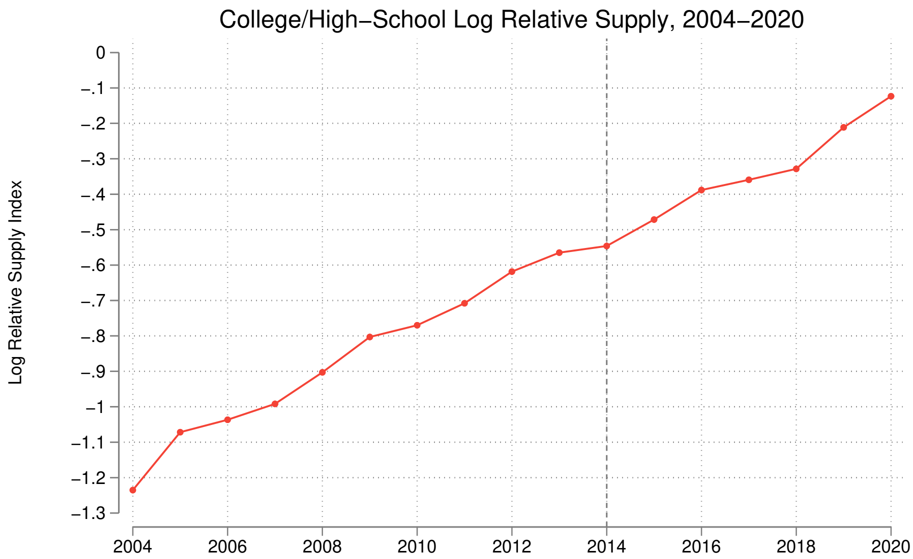
After 2010, increase in the college premium is stopped which can be seen in 3, but it's sharp decline started after 2014. A college premium of 41 log points implies that, in 2004, the earnings of an average college graduate were 50 percent higher (i.e., $\exp(0.41) - 1 \simeq 0.50$) than the average wage of a worker without college diploma. After reaching its initial level around 2017, the college premium remained around 44 percent in 2020 We present a different form of figure 3. The **??** shows the picture of two different experience cohorts.

College premium, which can be considered as the valuation of skills determined trough the market forces, is linked to it's supply, among other factors. While figure 4a depicts the premium of education, figure 4b is showing the situation in terms of labor supplied by each educational level.

Figure 3: College-High-School Wage and Supply Dynamics, 2004-2020



(a) Composition Adjusted College/High-School Log Real Weekly Wages Ratio, 2004-2020

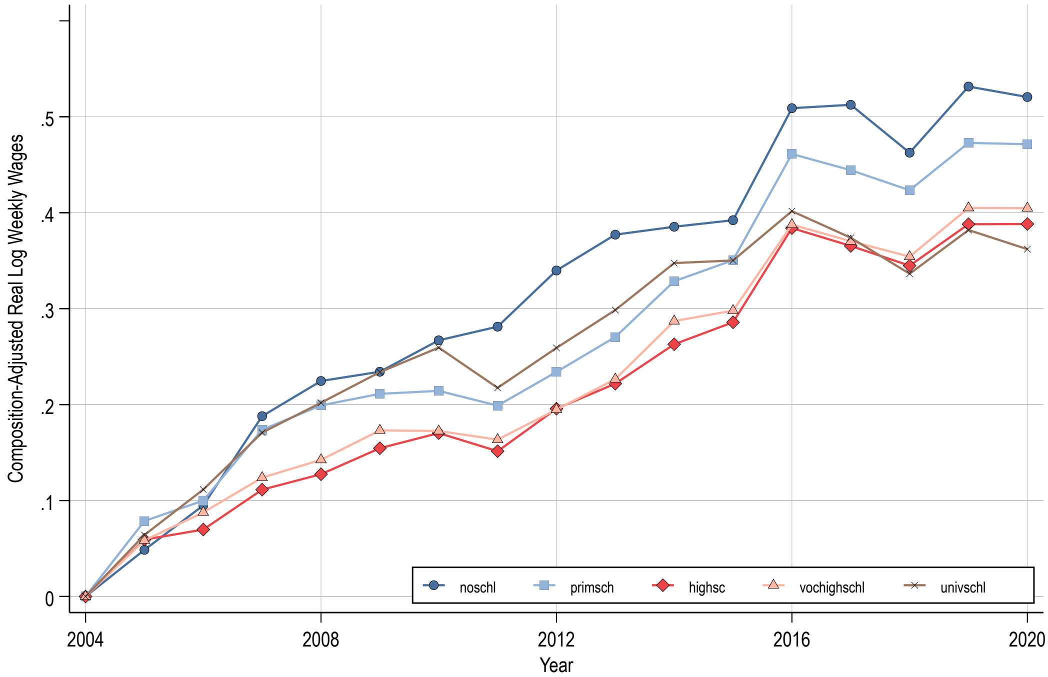


(b) College/High-School Log Relative Supply, 2004-2020

Source: Author's calculations by using efficiency units.

Growth in the level of college graduates shows a secular form, reaching to almost half of the work force in 2020. Initial level of relative labor supply was three college graduates for every ten worker who did not complete or attend to any college edučtion. A different version of Figure 4 is presented individual plots of female and male data is presented in Appendix Figure 16.

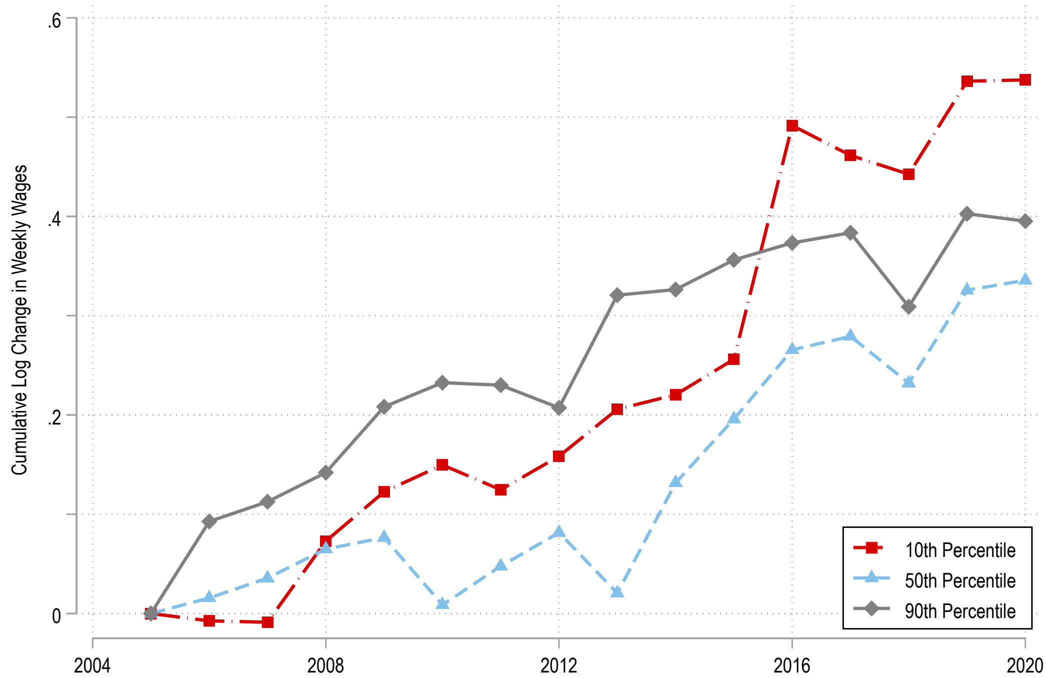
Figure 4: Composition Adjusted Log Real Wages of Education Cohorts (2004-2020)



Source: Authors's calculatiions using HLFS (2004-2020). Calculation of the labor supply is based on the reported usual weekly working hours of all persons aged 14-64 who are employed and either recieving a monthly wage or a salary. The real log weekly wages for each education category is the weighted average of the relevant composition adjusted cells using a fixed set of weights equal to the average employment share of each group. Predicted nominal wages are deflated by the GDP deflator. (noschl: below primary school, primsch: primary school, highsc: high school, vochighschl: vocational high school, univschl: college)

Wage premium predictions give little information on the real wage levels of different skill groups. Declining college premiums might be explained by a faster rise in non-college wages. Together with the steady growth of the labor force holding a college diploma, growth speed of college graduated labor force's wage levels stayed relatively low, as we see in the figure 3. Moreover, Figure **??**, gives more detailed information on real earnings of five education groups and two gender groups. Figure plots the evolution of log wages throughout the period under study. Each series is normalized to zero in the beginning year. Values are corresponded to the log changes of wages relative to it's initial level, which is 2004. Starting from the beginning years, wage increases for workers with primary school diplomas and below are faster than for high school graduates. Although college-graduated workers' wage increases align with the unskilled labor for the first 5 years, their wage levels stagnated after 2014.

Figure 5: Cumulative Log Real Wage Growth at the 90th, 50th and 10th Wage Percentiles (2004-2020)



Source: Labor Force Survey cross-sections from 2004 to 2020 are pooled. Similar to (Işık, Orhangazi, & Tekgüç, 2020) the sample data cleaned to obtain full-time workers who have permanent jobs and are earning more than 75% of minimum wage for each particular year.

2.2 Shift-share Decomposition

An indispensable explanation for the phenomenon of employment polarization asserts that the configuration of industries has undergone a transformation, gravitating towards economic sectors that exhibit diminished reliance on "routine" occupations, while concurrently embracing a greater reliance on "abstract" and "manual" tasks. To see if this explanation fits into Turkish labor market, we use a shift share decomposition method with a standard form, in line with the literature (Acemoglu & Autor, 2011; Bárány & Siegel, 2018; Goos, Manning, & Salomons, 2014). The overall change in employment distribution of each occupation j, between year 0 and t can be expressed as:

$$\begin{aligned} \Delta E_{jt} &= \sum_k \Delta E_{kt}\lambda_{jk} + \sum_j \Delta\lambda_{jkt}E_k \\ &\equiv \Delta E_t^B + \Delta E_t^W, \end{aligned} \tag{3}$$

Herein, ΔE_{jt} denotes the change in the overall share of employment in occupation j over time period t. ΔE_t^Bdenotes the change in the share of employment in occupation j which is attributed to alterations in industrial composition. The term ΔE_t^W denotes variations in the employment proportion of occupation j, corresponding to shifts occurring within-industries. $\Delta E_{kt} = E_{kt_1} - E_{kt_0}$represents the change in industry k's employment share during time t. $E_{kt} = (E_{kt_1} + E_{kt_0})/2$ is the mean employment distribution of industry k across time span t of four years. $\Delta\lambda_{kt} = \lambda_{kt_1} - \lambda_{kt_0}$ quantifies the change linked to the occupation j's share employment in industry k over the specified time interval t, and $\lambda_{jkt} = (\lambda_{jkt_1} + \lambda_{jkt_0})/2$ represents the average employment distribution of occupation j within industry k during time t.

In Table 3 we summarize the results. First four columns splits the observation period into four equal segments, followed by subsequent column showing the results for the extended time period. Evidently, there is a clear pattern of occupational employment share shifting towards Clerical and Managerial occupations, and elementary occupations from occupations in manufacturing. This is in line with RBTC hypothesis which posits a transfer of employment share towards more skilled and less skilled occupations from middle skilled occupations.

The sharp rise in the employment share of clerical, administrative and sales occupations during the interval of 2012-2016, was primarily accounted for by the growth in employment within industries. This change can be attributed to the adaptation process undertaken by TurkStat, leading to the introduction of new occupational classifications in 2012. Notably, workers previously categorized as managers in small enterprises (ISCO 13) transformed, transitioning to roles such as salespersons and demonstrators, which are classified as ISCO 53 within the updated occupational coding system. A corollary observation is discernible in the reduction of total employment within non-routine cognitive occupations, a shift predominantly explicable by changes occurring within industries. This indicates that the workers previously designated as managers, subsequently transitioned to sales jobs as a direct outcome of the aforementioned coding transition.

The decline in blue collar routine manual jobs was counterbalanced by the increase in clerical and elementary jobs within the aggregate employment distribution. Notably, one third of the reduction in blue-collar jobs can be attributed to the inter-industrial shift of workforce allocation, primarily towards the service sector. It is noteworthy that this inter-industrial redistribution has exhibited a gradual deceleration over the past decade. Within industry component accounts for fifty percent of the transformation observed in elementary jobs. This implies that the augmentation in the overall employment share within sectors that exhibit a demand for unskilled labor has been responsible for half of the employment variation.

Table 3: Decomposition of Changes in Terms of Employment Shares in Broad Occupational Categories

	2004-2008	2008-2012	2012-2016	2016-2022	**Total**
Professional, Managerial, and Technical Occs. (non-routine cognitive)					
Total Δ	0.75	-0.91	-2.75	2.53	-0.09
Between Δ	0.20	-0.18	0.17	0.24	0.11
Within Δ	0.55	-0.73	-2.93	2.29	-0.20
Clerical, Administrative and Sales Occs (routine cognitive)					
Total Δ	1.08	0.30	5.33	-0.65	1.51
Between Δ	0.23	0.21	0.40	0.34	0.30
Within Δ	0.84	0.08	4.93	-0.99	1.21
Production, Craft, Repair and Operative Occs (routine manual)					
Total Δ	-3.38	-1.71	-2.74	-1.38	-2.30
Between Δ	-0.09	-2.55	-0.82	-0.01	-0.87
Within Δ	-3.28	0.84	-1.91	-1.37	-1.43
Elementary (non-routine manual)					
Total Δ	1.54	2.32	0.15	-0.49	0.88
Between Δ	0.6	-0.33	-0.00	0.10	0.46
Within Δ	-0.16	-0.06	-0.35	0.27	0.42

Source: Labor Force Surveys of 2004, 2008, 2012 and 2022. Each set of three rows (Total, Industry, Occupation) shows the changes in employment shares in four broad occupational categories, which are constructed according to their principal task content. Time intervals divide the study period into four equal periods. With this structure, changes in employment shares decomposed into between and within-industry components. The decomposition uses 8 broad occupational categories (agricultural workers are excluded from the sample) and 17 broad industry category. These groups are harmonized accordingly to obtain a full sample. We do not impose any exclusion criteria, except for the omission of part-time workers. This decision is based on the heterogenous presence of non-permanent workers and individuals earning wages below the monthly minimum wage level across occupation categories.

Goos et al. (2014, hereafter, GM) argue that the SBTC literature almost entirely relies on the within-industry component on explaining skill upgrading. However, between-industry component of employment changes can be driven by routinization. Because, routinization is more substantially impacts industries of routine occupations and displaces labor towards other industries. Therefore, according to GM, RBTC will cause a between-industry shift in blue-collar occupations. Despite the substantial effect of between industrial shifts coming from the previously mentioned transition process, about one third of the total shift can be attributed to change in industrial composition.

Table 4 documents the analysis similar to what is shown in table 3, but with a different structure used by GM. They mapped the Routine Task Intensity Index from Autor and Dorn (2013) to occupational classification used by European countries. According to their mapping, the most routine intensive occupation is office clerks (ISCO 41), while the least routine intensive occupational category is managers of small enterprises (ISCO 13). In column 3 of table 4 their RTI index is reported. For 21 occupations ranked by their mean wage in 2004 (a broadly used proxy for skill level), column 1 and column 2 presents average share of employment in 2004 and employment change from 2004 to 2012, respectively. GM reported a substantial decline in middle paying occupations and a substantial rise in high paying and low paying occupations. Table 4 presents some contrary trends in average employment shares. While middle paying occupations and high paying occupations experienced substantial employment growth in the time period, low paying occupations accounts for all the growth in other sectors with a %10 decline in employment share.

Table 4: Changes in the Shares of Hours Worked, 2004-2012

Occupations ranked by mean 2004 wage	ISCO88 Codes	2004 Share (1)	% change (2)	RTI (GM) (3)	within (4)	between (5)
High Paying Occupations		19.38	5.78	-0.64	2.94	2.84
Life science and health	22	1.13	0.71	-1.00	0.44	0.27
Engineering	21	1.47	0.76	-0.82	0.62	0.14
Corporate managers	12	2.93	1.68	-0.75	1.36	0.33
Other professionals	24	3.30	0.41	-0.73	0.11	0.30
Health associates	32	1.98	-0.66	-0.33	-1.59	0.93
Other associate	34	4.95	1.65	-0.44	1.02	0.63
Engineering associate	31	3.63	1.22	-0.40	0.98	0.24
Middle Paying Occupations		45.49	6.17	0.04	0.78	5.39
Managers of small enterp.	13	1.10	0.00	-1.52	-0.12	0.11
Office clerks	41	8.92	2.59	2.24	1.34	1.25
Customer service clerks	42	3.04	0.79	1.41	0.51	0.28
Personal, protective service	51	11.04	2.42	-0.60	2.03	0.39
Metal, machinery	72	6.78	-0.23	0.46	-0.52	0.28
Extraction and building	71	4.98	0.84	-0.19	-2.01	2.85
Drivers, mobile plant	83	9.63	-0.24	-1.50	-0.45	0.22
Low Paying Occupations		35.13	-10.62	0.60	-1.04	-9.58
Stationary plant	81	1.67	0.07	0.32	0.04	0.03
Precision, handicraft, craft	73	1.07	-0.26	1.59	-0.47	0.22
Sales and service	91	7.41	-11.53	0.03	-1.05	-10.48
Machine operators	82	8.94	0.90	0.49	1.08	-0.18
Laborers	93	3.69	0.91	0.45	1.88	-0.97
Models, salespersons	52	5.50	2.70	0.05	1.60	1.10
Other craft	74	6.85	-3.40	1.24	-4.10	0.70

Source: Author's calculations using Routine Task Intensities supplied by Goos et al. (2014).

2.3 Polarization of Turkey's Labor Market

In order to document polarization, we start with a well-established methodology used by Acemoglu and Autor (2011); Autor et al. (2006); Goos and Manning (2007), and Autor and Dorn (2013). We first sort 2-digit occupations into percentiles by using median hourly wages[5] of each occupation from 2004 and 2012

[5]We assume that the median hourly wage of each occupation serves as an indicative measure of the price the market is willing to pay in exchange for the productive output it generates. Using mean wages or mean years of educational attainment would give similar results.

LFS datasets separately. We distribute sorted occupations into percentiles by using their relative labor supplies as weights. These labor supplies are quantified by each occupation's contribution to the total hours worked in the dataset. Thus, we create a sample of 100 observations, each corresponding to a percentile of employment from the base year. After we similarly compute each occupation's share in the final period, we merge these two samples and predict the employment share change corresponding to each percentile. In compliance with the literature we apply a locally weighted smoothing regression with a bandwidth of 0.3[6] to mitigate the impact of outliers and reveal the overarching trend we seek to uncover.

As noted by Goos and Manning (2007), one might be concerned that the ranking of jobs' median wage could experience substantial fluctuations over time, potentially leading to patterns of employment growth that are highly sensitive to the specific time point at which we observe the median wage for a particular occupation. To overcome this concern, we ranked occupations by their median wage at each point of time and observed that the changes in the distribution were are not significant. This also indicates the fact that the wage structure of occupations maintains stability over time.

Another notable concern might emerge from our sample's relatively constrained variety of the occupational coding system. Other studies employing a similar methodology to illustrate employment polarization (Acemoglu & Autor, 2011; Autor et al., 2006; Goos & Manning, 2007) exploits datasets with richer taxonomy of occupations. As a consequence, each percentile of employment comprises multiple occupations, which helps reveal the general trend, rather than local assessments. To address this limitation stemming from the LFS dataset, we plot the observed changes along with the predicted values from the smoothing regression. Therefore, we aim to compensate for this limitation by analyzing the individual impacts of occupations on the general trend.

The graphs are structured to offset all the employment change trough 1st to 100th percentiles. This means that, without the smoothing regressions, we would observe a fifty percent rise and a fifty percent decline in employment shares, as each bar below the origin indicates a change relative to each bar above the origin.

During the first half of the study period, depicted in Figure 7a, we observe a modest growth in the second decile whereas a substantial expansion is witnessed in employment shares within the fifth decile. Conversely, the first decile undergoes

[6] The bandwidth level of a smoothing regression corresponds to the span of influence for neighboring data points in the regression estimation. A smaller bandwidth puts more weight on local patterns, while a larger bandwidth includes a broader range of data points, which can result in a smoother but potentially less sensitive fit.

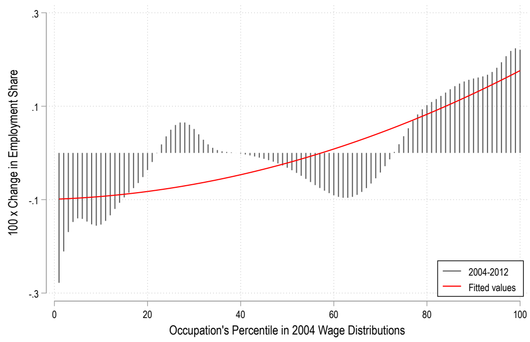
a large amount of decline in employment, while there is moderate a reduction between 40th and 80 percentiles. We have highlighted the prevailing trend by plotting the fitted values derived from the quadratic regression. Visual cues from the plot indicate a positive correlation between employment growth and the wage level observed in the base year.

In Figure 7b a discernible pattern emerges where the employment decline in the first decile is attributed to the influence of two distinct occupations. In particular, the initial three percentiles corresponds to the agricultural laborers (ISCO 92), whose employment share declined 38%. As we progress from the 11th to the 19th percentile, the composition shifts to encompass food processing and textile workers (ISCO 74). In contrast, intermediary percentiles comprise salespersons and demonstrators (ISCO 52), whose employment share increased nearly 10%. This pattern closely resembles an analogy of structural transformation, underscoring the evolving landscape of occupational distribution. Employment shifts towards the service sector from manufacturing and agriculture is an overarching trend maintains for several decades which is widely discussed in the labor economics literature. This trend would be more visible if we consider the transformation the of occupational coding scheme that occurred in 2012. When TurkStat switched to ISCO08 from ISCO88, a sudden jump occurred in the employment share of service occupations, particularly ISCO 52 and ISCO 53. However, this abrupt change cannot be observed in Figure 7b, as we followed the occupations' shift from ISCO88 occupation codes in the initial period. While a more comprehensive analysis is provided in the data section, it is important to highlight that the growth in the employment of salespersons could potentially have been significantly larger if TurkStat's transition process had been smoother.

Another interesting pattern emerges when observing Figure 7b and 7a. In the latter half of the wage distribution, a nearly monotonic trend of employment growth is evident. The clear shift from employment decline towards employment growth aligns with the start of the percentiles (74th percentile, specifically) allocated to customer service clerks (ISCO 41). In contrast, the preceding percentiles are attributed to drivers and mobile plant operators, which experienced a decline in employment.

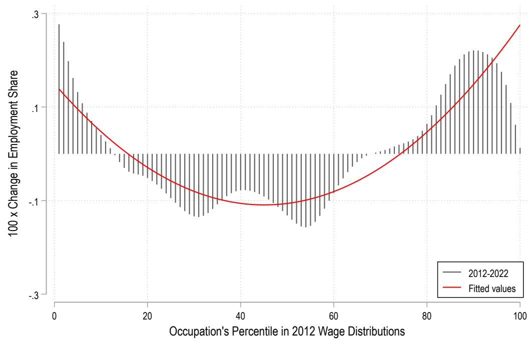
In Figure 7c and Figure 7d, notable patterns emerging both in the middle of the 2012's wage distribution (between 20th and 60th percentiles) and in the fifth decile. A substantial employment growth similar to the trend observed in the earlier period depicted in Figure 7a is evident in the highest decile. However, the most intriguing observations lie within the middle percentiles (20th to 60th), which appear to exhibit a pattern similar to the hollowing out of the middle class observed in (Autor & Dorn, 2013).

Figure 6: Smoothed and Observed Changes in Occupational Employment Shares

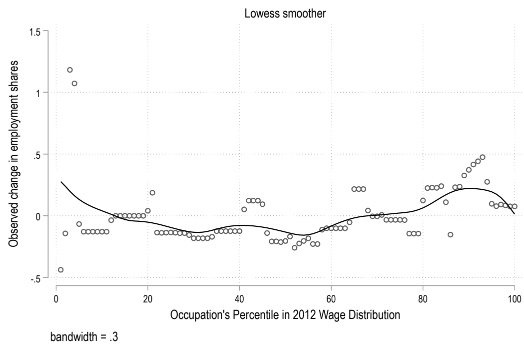


(a) Smoothed Changes (2004-2012)

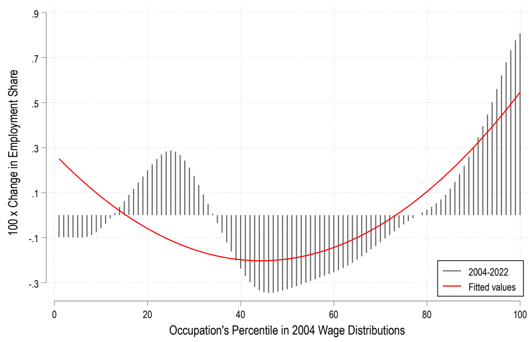
(b) Observed Changes (2004-2012)



(c) Smoothed Changes (2012-2022)



(d) Observed Changes (2012-2022)



(e) Smoothed Changes (2004-2022)

(f) Observed Changes (2004-2022)

Source: Author's calculations using 2004, 2012 and 2022 waves of HLFS. A smoothing regression (bw: 0.3) applied to follow the trend.

As the structural transformation is so evident, it allows us to distinguish the percentiles associated with service occupations from those linked with manufacturing occupations by observing the points above and below the zero line. Notably, the 5 percentile points emerging after the 40th percentile correspond to cleaners and helpers (ISCO 91), exhibiting a moderate growth rate. Conversely, the two deciles before and after ISCO 91 are positioned below zero line and corresponds to occupations within the manufacturing sector.

The situation is less clear in the first decile as depicted in Figure 7d. Excluding the first and fifth percentiles, all the intervening percentiles are associated with personal service workers (ISCO 51 and ISCO 53) and sales workers (ISCO 52). Notably, personal care workers (ISCO 53), constituting a two percent of employment, experienced an extraordinary growth rate of over 100%. In contrast, jobs such as travel attendants, cooks, waiters, and hairdressers (classified as ISCO 51) observed a decline in employment share, dropping from 6.6% to 5.5%. Meanwhile, the employment share of sales jobs remained steady at their 2012 level.

From Figure 7e and Figure 7f, we can track the general pattern of transformation in employment over the past two decades. Similar to the first period, starting from around the 40th percentiles, a monotonic trend emerges. Manufacturing jobs (ISCO 7 and ISCO 8) experienced a substantial decline of 12% in total employment share, a trend that is visually apparent from the diminishing employment between the 40th and 80th percentiles. The portion of employment previously held by the manufacturing sector jobs has been redistributed between occupations situated at the upper tail of the wage distribution, in particular, managers and professionals, in conjunction with service jobs concentrated around the 20th percentiles.

2.4 Calculating Task Contents

In the first part of this subsection, We'll introduce a summary index of routine task activities. Following Autor and Dorn (2013); Autor et al. (2006), by averaging the scores of non-routine cognitive tasks we aggregate them into an abstract task category. In addition to that, by averaging the scores of routine tasks we created a routine task category. Finally, by synthesizing these three task categories we obtain a composite measure of routine task intensity RTI for each occupation, which has the formal representation as follows

$$RTI = ln(T^R_{kt}) - ln(T^A_{kt}) - ln(T^M_{kt}), \tag{4}$$

Whereby, T^R_{kt}, T^A_{kt} and T^M_{kt} are, respectively, inputs of routine, abstract and manual task for each occupation k and year t. Our summary measure RTI exhibits a positive correlation with the prominence of routine tasks within an occupation, while displaying a negative correlation with the prevalence of abstract and manual tasks within the same occupation.

Table 5: Task Intensity of Major Occupations Categories

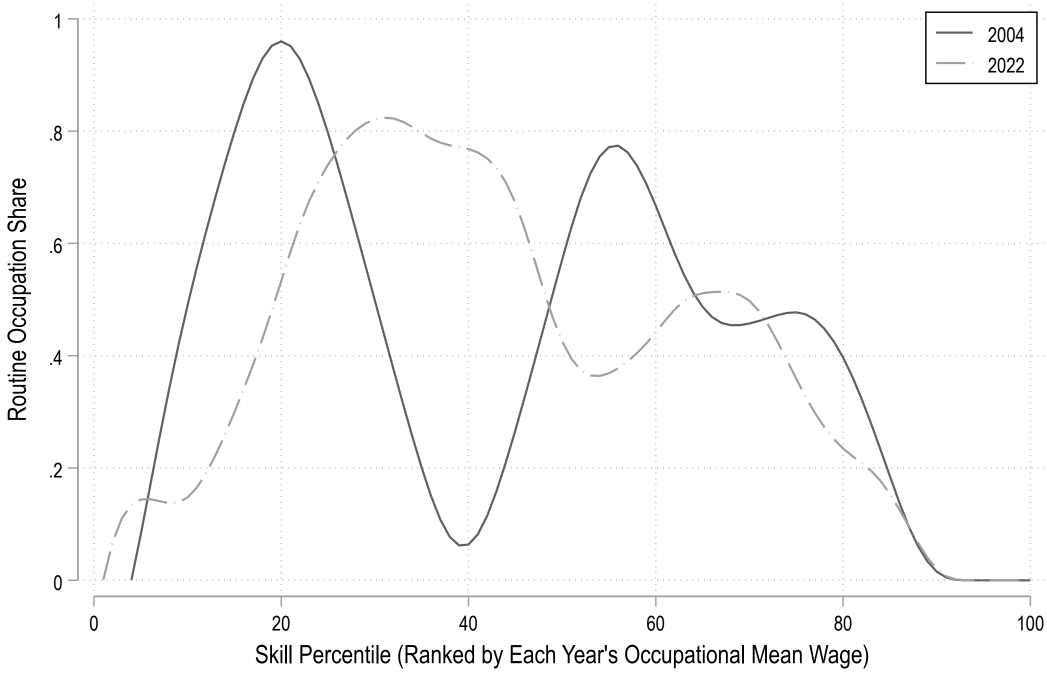
	RTI index	Abstract tasks	Routine tasks	Manual tasks
Managers/Legislators	-	+	-	-
Professionals	-	+	-	-
Technicians	-	+	-	-
Clerks	+	-	+	-
Service and sales	+	+	-	-
Craft and related trade	-	-	+	+
Machine operators	+	-	+	+
Elementary occupations	+	-	+	+

Notes: The table constructed by following the work of Autor and Dorn (2013). The plus sign indicates that the average value of particular task for that major occupation category is greater than the average. Minus sings indicates that the opposite. Gray shaded boxes are signs of that particular occupations' dominant task intensity.

In table 5 we summarized average task intensities of major occupational categories (agricultural workers are excluded). Whit this exercise, we can elaborate on general occupational task dimensions. As we going down the skill distribution, routine intensities are increasing except for the construction workers who are grouped under craft and related trade category, and manual tasks are becoming more dominant.

To make a more detailed comparison between routine task intensities and skill levels, we followed Autor and Dorn (2013) and separated occupations according to their place in the routine index distribution and defined the occupations in the top 1/3 as routine intensive. As we can see from figure 7, the share of routine jobs are the lowest at 1st percentile and after 80th percentile. Comparing this with Figure 7a which plots the employment growth of skill percentiles between 2004 and 2012, yields very interesting results. In each quintile of skills, if there is a rise in routine occupation share, there is a decline in employment share, and vice versa. The visual inspection of routine employment shares reveals correspondence with Figure 7c, which plots the second period's employment growths. Between 20th and 60th percentiles in 7c, employment decline matches to the increase in routine employment share in Figure 7. The categorization of routine employment share and more detailed statistics are displayed in Appendix Table A4.

Figure 7: Share of Routine Occupations by Occupational Skill Percentile



Notes: To allow time variation in task measures, we used waves of O*NET data corresponding to each year (O*NET 7.0 for 2004, and O*NET 17.0 for 2012). Also we use ISCO88 occupational coding scheme for the year 2004, and ISCO08 occupational codings for the year 2012. The allocation of occupations into percentiles was predicated on their respective positions within the wage distribution for each corresponding year. Applying an exclusion criteria similar to Figure 6, the data was subjected to refinement, yielding resilient metrics for occupational alignment across wage percentiles. Specifically, individuals such as farmers and workers without available wage information during the survey month have been excluded. Mean wage levels for each occupation category was used to determine the order of occupations in percentiles. Furthermore, we applied a smoothing regression with a bandwidth level of 0.3, aiming to present a visually coherent representation of the overarching trend.

Table 6: Means and standard deviations of O*NET task measures for four broad occupational groups in 2015

	Professional, Managerial, Technical	**Clerical, Sales**	**Production, Operators, Elementary**
	Males and females combined		
Non-routine cognitive			
Non-routine cognitive analytical	1.59	-0.23	-0.58
Non-routine cognitive personal	1.22	0.15	-0.71
Non-routine manual			
Non-routine manual physical	-1.05	-0.56	0.92
Non-routine manual personal	1.10	0.51	-0.92
Routine			
Routine cognitive	-0.57	0.31	0.08
Routine manual	-1.08	-0.60	0.97
Routine task intensity	-1.33	0.15	0.55

Source: Author's calculations based on the methodology described above.

In Table 6, first three major occupational categories are intensive in non-routine analytical and interpersonal tasks such as solving problems, reading and news and professional journals, supervising and giving speeches to others. Workers in Clerical and Sales occupations (ISCO 4-5) are performing tasks which on average, have more routine intensity than high skill workers. However, there is a substantial difference in routine intensity of these middle skills occupations. While clerical workers are attained to tasks with high routine cognitive intensity, such as book keeping or calculating, sales and service workers are doing non-routine cognitive and non-routine manual personal tasks which requires advanced interpersonal relationship skills.

Workers in occupations coded at the lower end of occupational distribution are distinctly related to routine and manual tasks which have the highest routine task intensity. Tasks in elementary occupations are substantially higher in routine intensity and lack of cognitive elements.

In order to analyze employment by task intensities, we allocate each job a composite task measure, using the 2004 LFS and 2004 O*NET as a reference point. Given that each occupation has multiple dimensions concerning task requirements, it is imperative to establish a rule-based decision-making framework to accurately allocate a task to each occupation. Adopting from Fonseca, Lima, and Pereira (2018) we allocate each occupation to a task for which the occupation ranks highest in intensity. To present formally, let each occupation j in task m have their rank denoted as $rank_{jm}$. Occupation j is considered to be more intensive in task m if $rank_{jm}$ > rank $rank_{ik}$, where $k \neq j$. We applied the procedure for each occupation separately by utilizing a simple sorting algorithm with a few exceptions. Agricultural occupations are excluded, since their shares in services and manufacturing would potentially be misleading to interpret. Additionally, managers of small enterprises are excluded from the sample for two primary reasons. Firstly, their employment share exhibited a continuous rise until the occupational coding transition in 2012, followed by a nearly 5% decline with the introduction of the new coding scheme. Secondly, the reported weekly working hours and wages for this subgroup are notably distinct from the sample average, introducing incompatibilities. Furthermore, observations associated with ISCO 33 were omitted due to their limited representation, resulting from an insufficient number of observation. The results are presented in Table A10.

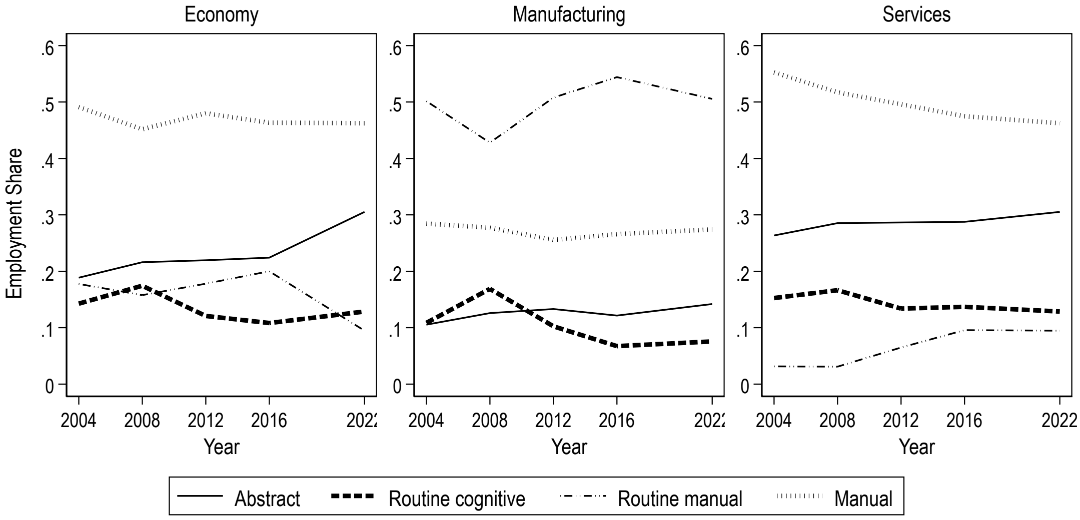
Since tracking the employment share of each occupation beyond 2012 is not feasible, we adopted a similar methodology as described earlier, but with 2012 as the base period, utilizing the 2012 LFS and O*NET dataset. Nevertheless, another challenge arises from pooling two data periods when aiming to analyze the complete sample period, stemming from the abrupt change that occurred in 2012, as elaborated in the data section. Our approach to address this concern involves a partially compromising the observed values in 2012. Given the lack of comprehensive information for 2012, apart from two variables indicating ISCO08 and ISCO88 codes for each occupation, we computed employment changes for the two periods separately using distinct occupational classifications. Subsequently, we merged the outcomes by calculating the average of the two samples for 2012. This approach enabled us to achieve a more gradual transition between the two periods, albeit at the cost of giving up the observed values for 2012.

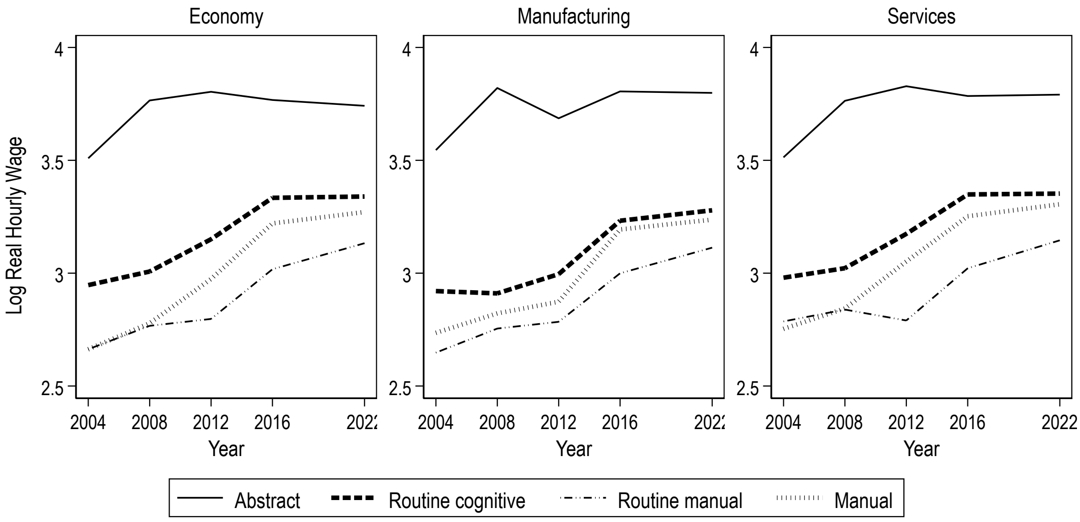
Using the above procedure, we predicted trends in employment shares by selected task for the economy, manufacturing and services. Note that we include agricultural workers and construction workers in the economy. Depicted in Figure 8a approximately half of the workers classified under the manual category for both the services and the entire economy. Notably, the manual task proportion witnessed a reduction of 10% in the services sector and 5% in the economy.In spite of manual jobs, routine manual jobs are more prevalent in the manufacturing sector. When combined with manual jobs, their collective representation accounts for almost 80% of the manufacturing sector's workforce.

Furthermore, within both the manufacturing and services sectors, the share of routine cognitive tasks reaches around 18% in 2008, followed by a nearly monotonic subsequent decline over the sample period. In contrast, the trend for routine manual jobs in manufacturing and manual jobs in services follows an opposing trajectory.

Figure 8: Employment and Wage Changes by Task and Sector (2004-2022)

(a) Employment Changes by Sector (2004-2022)





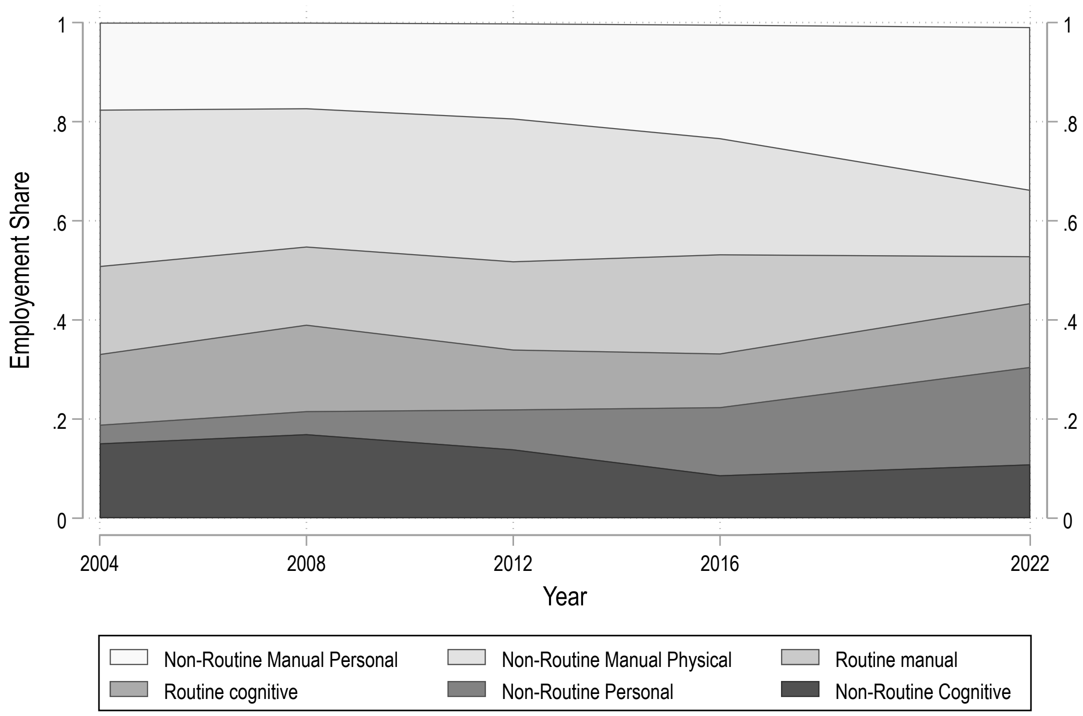
(b) Real Wage Changes by Sector (2004-2022)

Notes: Employing a slightly altered framework compared to Figure 7, we harnessed two waves of O*NET data (O*NET 7.0 for 2004, O*NET 17.0 for 2012) to derive task measures. Subsequent to the independent integration of standardized task measures into the 2004 and 2012 datasets, we assigned each occupation to a composite task measure for which the occupation ranks highest in intensity. By aggregating each occupation's labor share to the occupation's principal task component, we constructed a dataset comprising employment shares for each task measure. Thus, this approach allows us to trace the employment share of each composite task measure by simply connecting each wave of data (2004, 2008, 2012, 2016 and 2022) by using their occupational employment shares.

While in Figure 8a, we can observe an ascending trend in the category of abstract tasks, as reflected in the relative shares of employment. However, the trajectories for the remaining task categories, do not exhibit a consistent monotonic pattern. In terms of log real weekly mean wages, an interesting pattern emerges. In accordance with Figure **??** and Figure 4,jobs characterized by a significant intensity of cognitive element, displayed no real wage growth after 2016, whereas, jobs with manual task component underwent a notable surge in real wage growth rates over the study period, plotted in Figure 9b.

Figure 9, plots a more detailed version of Figure 8a, by employing a stacked area graph scheme to display relative shares of tasks summing up to a total of 1. A striking pattern emerges from Figure 9, which divides abstract and manual tasks into their subcomponents. The jobs with personal task component (Non-routine manual personal and Non-routine personal) in total, were just above 20% of total economy, in terms of total hours worked in 2004. However, by the year 2022, this share has undergone a remarkable growth, leading it to encompass 55% of the total hours worked within the economy.

Figure 9: Employment by 6 Task Categories for All Sectors (2004-2022)



Notes: Author's calculations based on O*NET data and corresponding waves of HLFS.

So far, our analysis has centered around task content data from occupations in the United States, which aligns with the predominant approach taken by numerous studies scrutinizing the US labor market (Acemoglu & Autor, 2011; Autor & Dorn, 2013; Autor et al., 2006, 2003; Firpo, Fortin, & Lemieux, 2011; Spitz-Oener, 2006), as well as similar researches in Europe (Aedo, Hentschel, Luque, & Moreno, 2013; Fonseca et al., 2018; Goos & Manning, 2007; Goos et al., 2009, 2014; Hardy, Keister, & Lewandowski, 2016a, 2018). The task content data used in these studies is sourced from two primary databases: the Dictionary of Occupational Titles (DOT), which dates back to 1939, and the Occupational Information Network (O*NET), initiated in 2003. Both of these databases provides comprehensive and periodically updated information regarding the specific tasks linked to the occupations within the United States. Unfortunately, no comparably comprehensive dataset has been systematically collected for labor markets in other countries. As a result, studies examining non-US labor markets often utilize the US task database and rely heavily on the assumption of task content equivalence across different countries.

Aiming to account for country specific task content of occupations, we adopted the methodology described in Lewandowski, Park, Hardy, Du, and Wu (2022); Rica, Gortazar, and Lewandowski (2020) in order to develop a task content metric specific to Turkey's labor market by using the Programme for the International Assessment of Adult Competencies (PIAAC) survey. Different from O*NET Data, this survey comprises worker-specific information on daily tasks at work. Moreover, the composite task measures are compatible with the well-established job task measures used in Acemoglu and Autor (2011).

Our measure for non-routine cognitive analytical tasks incorporates questions in PIAAC relating to problem-solving, reading news, engaging with professional journals, solving problems, and programming. Meanwhile, the measure for non-routine cognitive interpersonal tasks relies on the activities such as supervising others and making presentations. The routine cognitive task measure is based on sequentiality, where the cognitive aspect stems from the ability to rearrange task order. This is quantified by factors such as the inability to change the order of tasks (reversed), form completion, and giving speeches or presentations (reversed, denoting no speeches or presentations). To compute the routine task intensity (RTI) using the PIAAC survey, we apply the formula specified in equation 4. In order to prevent non-positive values in the logarithm, we add 1 for each task.The occupation specific measures are provided in Figure 18. The table can be found in

Analyzing the daily tasks that people undertake improved the understanding of micro-level behaviors of workers to explain structural occupational changes. Labor economists, collected information on workers' tasks and used it for their analyses on the technology's role in explaining job polarization, structural change and wage inequality. However, this task-centric approach introduces its own set of challenges, most prominently concerning the quantification and measurement of tasks. Unlike skills, which can often be approximated using proxies such as education or experience, tasks are intricately tied to the specific requirements inherent to distinct occupations. Furthermore, the lack of a universally accepted taxonomy for task classification compounds the measurement challenge. Additionally, consistently collected data sources across diverse labor markets are scarce, which further complicates the task analysis landscape (Biagi & Sebastian, 2020). To illustrate the issue, consider the case of "non-routine manual" major task category. Across, various studies, this task category operationalized trough different task components: "hand-eye-foot coordination"(Autor & Dorn, 2013), (ii) time spent performing physical activities" (Autor & Handel, 2013).

As pivotal contribution to the field, Autor et al. (2003) introduced a taxonomy major task categories based on two main axes: Routine vs. non-routine, and cognitive vs. manual. Subsequently, researchers such as Autor and Dorn (2013); Autor and Handel (2013) used a threefold classification: Abstract, routine and manual. Threefold classification aggregates non-routine tasks to obtain abstract tasks.

First we apply the methodology of Acemoglu and Autor (2011) by using 3 O*NET data sets for 2004, 2012 and 2022 to obtain 5 major task categories from 16 subset of tasks which are presented in Table A7. Nonetheless, while utilizing varied datasets enhances our capacity to capture temporal shifts in task intensity across occupations, there are two major shortcomings. Firstly, each wave of the O*NET dataset focuses on the U.S. labor market and lacks dimensions specific to labor markets of different countries. Secondly, the O*NET dataset is constructed through the lens of experts who assign task values based on the requisites of particular occupations. This expert-driven perspective potentially introduces bias, as it lacks the workers' perspective on their occupations (Aedo et al., 2013).

By using the methodology above, we create a data set, in which each occupation i is defined by a vector of tasks, X_{ik}, for the year k, and each occupation i has a task intensity value for each of the five skills which are not exclusive. The structure is shown in the below matri

$$X_{ik} = \begin{bmatrix} X_{ik}^{Non-Routine\,Cognitive/Analyrical} \\ X_{ik}^{Non-Routine\,Cognitive/Interpersonal} \\ X_{ik}^{Routine\,Cognitive} \\ X_{ik}^{Routine\,Manual} \\ X_{ik}^{Non-Routine\,Manual\,Physical} \end{bmatrix}$$

Hardy et al. (2018) extended the ALM and AA task framework to encompass Europe by leveraging O*NET and EU-LFS data. Following their application, we identify a subset of five tasks from a set of sixteen distinct task requirements available within the O*NET data. These are, non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, routine manual, and non-routine manual physical tasks. To facilitate integration with out occupations dataset, we employed the crosswalk provided by Hardy et al. (2018). The formulation of each composite task measure involved the summation of the 16 task items, which subsequently underwent a standardization process to attain a mean of 0 and a standard deviation of 1. After having assigned each task item t to the LFS data, we apply a standardization procedure to achieve comparability over time, and between each composite task measure, following AA. The standardization process adheres to the following formula:

$$\forall i \forall j \in J \quad t_{i,j}^{std} = \frac{t_i - \mu_j}{\delta_j}, \tag{5}$$

$\boldsymbol{J}$, identifies the set of task items for $\boldsymbol{i}$ observation in the LFS which will be aggregated to obtain 5 composite task measures mentioned above. μ_j is weighted average and δ_j is the standard deviation of task item j. Weighted average and standard deviation of each task item calculated with the formulas below:

$$\forall i \forall j \mu_j = \frac{\sum_{i=1}^{N} t_{i,j} w_i}{\sum_{i=1}^{N} w_i}, \tag{6}$$

$$\forall i \forall j \delta_j = \left(\frac{\sum_{i=1}^{N} w_i (t_{i,j} - \mu_j)}{\sum_{i=1}^{N} w_i} \right)^{1/2}, \tag{7}$$

Whereby w_i is the weight attributed to the observation $\boldsymbol{i}$ int he LFS dataset. Following the standardization of 16 task items, we create 5 task measures by adding up the task items.

2.5 Estimation Strategy

The foundation for empirically analyzing the market's returns on investments in human capital is rooted in the Mincer earnings model (Mincer, 1974). Within this model, human capital is proxied by education and cumulative experience. Notably, the coefficient associated with the duration of schooling, as extracted from a logarithmic earnings regression, is construed as the compensatory differential for the income foregone during the years in education. If we assume unidimensional human capital and competitive markets, the law of one price becomes applicable: the comprehensive value of human capital should remain consistent across various occupations. These presumptions can be shown in a hedonic earnings model as the following:

$$lnw_i \quad = \quad \alpha + \delta_1 S_i + \delta_2 \mathbf{X}_i + \delta_3 Exp_i + \delta_4 Exp_i^2 + e_i, \tag{8}$$

wherein, w_i is the worker i's log hourly wage, $\mathbf{X_i}$ is a vector of individual-level covariates, S_i is years of educational attainment, while the Exp, stands for the potential years of job experience. The parameter $\hat{\delta_i}$ derived from the model estimates of a market return associated with each year in school. By incorporating the assumptions of negligible primary schooling costs and the efficient functioning of the market, the model's predictions indicate a convergence between the market interest rate and the equilibrium return rate of each year in school.

Can this model be extended to predict task prices using a wage regression as in Eq. 8? Autor and Handel (2013) address this inquiry by underscoring dissimilarities between tasks and education. Firstly, the tasks are not durable investment goods contrary to education, as the worker can modify task inputs according to a job's demands. Consequently, this adaptive self-selection process negates the existence of a direct correspondence between tasks and the human capital endowed within workers. Secondly, unlike education, the tasks are a high-dimensional bundle of activities in which the elements must be performed jointly to produce output.

To formally present the model of Autor and Handel (2013), let the worker i has a set of skill endowments $\mathbf{\Phi}_i = \{\phi_{i1}, \phi_{i2}, ..., \phi_{iK}\}$,as a vector of task efficiencies. Each element of vector $\mathbf{\Phi}_i$ is a strictly positive number measuring the efficiency of a worker i at task k. Since the worker i can perform ϕ_{iK} units of task k in a given time interval, the $\mathbf{\Phi}_i$ represents the worker's human capital stock, and her productivity in producing tasks is conditional on the human capital investments and the combination of other abilities.

Different from the standard Mincerian approach, the marginal productivity of education is not equal across sectors. However, the productive value of a task differs among occupations, which produce the output using the vector of task K. Therefore, the output of a worker i in occupation j is as follows:

$$Y_{ij} = e^{\alpha_j + \sum_k \lambda_{jk}\phi_{jk} + \mu_i},$$

whereby $\lambda_{jk} \geq 0 \ \forall \ j, k$ and $\alpha_j$is not strictly positive, since the marginal product of a worker's task production would yield negative values conditional on the insufficiency of skill endowments. If the workers wage is equal to her marginal product, the log wage equation can be written as:

$$w_i = \alpha_j + \sum_k \lambda_{jk}\phi_{jk} + \mu_i,$$

Within this production structure, if we allow for each worker to choose their occupation to yield the most output, which maximizes her earnings, her maximization problem will be as follows:

$$Y_i = \max_j\{Y_{i1}, Y_{i2}, ..., Y_{iK}, \} = \max_j\{\alpha_j + \Phi_i \Lambda_j'\},$$

where Λ_j is a vector denotes the production structure of occupation j, $\Lambda_j = \{\alpha_j, \lambda_{j1}, \lambda_{j2}, ..., \lambda_{jk}\}$. Within this model, the task returns are specific to occupation: $\partial w / \partial \phi_k \mid_{J=j} = \lambda_{jk}$.

Autor and Handel (2013) provides testable restrictions for their model to identify structural parameters underlying this model. Next, we summarize the two testable proposition and their specification for empirically testing them.

Proposition 1 *The covariance among task returns, and between task returns and the constant term cannot be uniformly positive.*

To test this implication, we conduct a series of estimations, as shown in the following equation:

$$W_{ij} = a_j + \delta_{jA} A_i + \delta_{jR} R_i + \delta_{jM} M_i + e_{ji}, \tag{9}$$

Where, the subscript "j" is indicative of different occupations. We estimate the Eq. 9 separately for each occupation with a minimum of 5 observations, The resulting estimated parameters from these regressions are preserved to form a dataset. This dataset is then employed to perform bivariate regressions among the components $\{a_j, \delta_{jA}, \delta_{jR}, \delta_{jM}\}$, with each regression being weighted by the employment size of the respective occupation, as in the following:

$$\begin{aligned} &\widehat{\delta_{jA}} = \alpha_1 + \gamma_1 \widehat{\delta_{jR}} + e_{12}, \quad \widehat{\delta_{jA}} = \alpha_2 + \gamma_2 \widehat{\delta_{jM}} + e_{13}, \\ &\widehat{\alpha_j} = \alpha_3 + \gamma_3 \widehat{\delta_{jA}} + e_{01}, \quad \widehat{\alpha_j} = \alpha_4 + \gamma_4 \widehat{\delta_{jR}} + e_{02}, \quad \widehat{\alpha_j} = \alpha_5 + \gamma_5 \widehat{\delta_{jM}} + e_{03}, \end{aligned} \tag{10}$$

Proposition 2 *To enable workers to positively self-select into occupation j based on their proficiency in task 1 and into occupation j ´ based on their proficiency in task 2, a fundamental requirement is that:*

$$\rho \quad < \quad min\left(\frac{\lambda_1}{\lambda_2'}, \frac{\lambda_2'}{\lambda_1}\right), \tag{11}$$

Where $\rho \ \leq \ 0$*, meaning that the workers abilities on different tasks are either uncorrelated, or negatively correlated.*

This proposition aligns the model with the principle of comparative advantage, where individuals select occupations that best use of their inherent strengths, leading to a more efficient allocation of labor resources. Therefore, the self-selection implies non-zero covariances between occupation-level task returns, and workers' endowments. To capture these covariances, Autor and Handel (2013) offers the following specification, in which the average task measures of each occupation interacted with the individual level task inputs:

$$\begin{aligned} W_i \quad = \quad & a + \delta_A A_i + \delta_R R_i + \delta_M M_i + \beta_A \overline{A_j} + \beta_R \overline{R_j} + \beta_M \overline{M_j} \\ & + \gamma_A A_i \times \overline{A_j} + \gamma_R R_i \times \overline{R_j} + \gamma_M M_i \times \overline{M_j} + \theta \mathbf{X_i} + \varepsilon_\mathbf{i} \end{aligned} \tag{12}$$

Most analyses on job tasks often conceptualize tasks as an occupational level construct. However, a notable advantage offered by the PIAAC (OECD, 2016) micro dataset is its provision of individual-level measures. This facilitates an exploration of the variability in job tasks within specific occupations, as well as an examination of the extent to which this variability is systematically associated with both worker-related factors and job-specific attributes. In the next section, we empirically test this model's implications.

3 EMPIRICAL ANALYSIS

3.1 Explaining Differences in Job Tasks

This section analyzes the degree to which the tasks performed by workers within their respective jobs can be explained by factors such as their human capital, demographic characteristics, and the technical requirements intrinsic to the job itself. These technical requirements are approximated through the utilization of detailed occupation dummies. Our analytical approach is based on descriptive Ordinary Least Squares (OLS) regressions, which are structured as follows

$$T_{ij} = \alpha + \delta_1 C_i + \delta_2 \mathbf{X_i} + \gamma_j + \lambda_i + \varepsilon_{ij} \tag{13}$$

Where the vector of $\boldsymbol{C}$ denotes the human capital measures (education, computer experience, job experience), vector $\mathbf{X}$, denotes the demographic variables (parents' educational attainment, age and gender), γ is a vector of 2-digit occupation dummies and λ denotes the vector of firm size (3 categories) and industry (21 categories in total) dummies. The reference group is a female with lower secondary or less education between the ages of 15-19, whose parents have not completed upper secondary school. The results of the estimation are presented in Table 8.

Table 8 shows significant associations with some variables. The even-numbered columns (2, 4 and 6) correspond to estimations with 2-digit ISCO08 occupation dummies. Including occupation dummies induces a substantial augmentation in the model's fit across all task categories. Notably, when the occupation dummies are included, the explanatory power reaches 35.5% for the abstract tasks. Furthermore, the education dummies are statistically significant for most of the regressions and their coefficients are increasing (in absolute terms) with more years spent in school. While the coefficients of education dummies are positive for abstract task scores, for the other two task categories, it takes negative values, indicating a notable positive correlation between abstract tasks and skills acquired during formal education, as the coefficient's magnitude increases with the years spent in school. Notably, the coefficients of education dummies are decreased in all the task categories, when we control for the occupation dummies. This observation indicates that the relationship between education and task categories depends on the occupational assignment. In particular, concerning manual tasks, introducing occupational dummies leads to the loss of significance in the association between educational attainment and manual tasks. Males lower use of abstract tasks persists with the occupation controls, but this is not the case for routine tasks. The occupational assignment primarily mediates the significance of the positive relationship.

Table 8: Estimation Results of Task Scores with Individual Characteristics

	Abstract		Routine		Manual	
	(1)	(2)	(3)	(4)	(5)	(6)
Human Capital						
Education dummy (base=lower secondary or less)						
Upper secondary	0.23***	0.13*	-0.13*	-0.04	-0.10	0.05
	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)
Tertiary 2-3 years	0.70***	0.50***	-0.51***	-0.30***	-0.18	0.06
	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.09)
Tertiary 4 years	1.05***	0.68***	-0.78***	-0.39***	-0.35***	-0.06
	(0.08)	(0.09)	(0.08)	(0.10)	(0.09)	(0.10)
Tertiary Master	1.39***	0.96***	-1.10***	-0.63***	-0.58***	-0.24
	(0.15)	(0.15)	(0.15)	(0.16)	(0.16)	(0.16)
No computer exp.	-0.30***	-0.20	0.40***	0.36***	0.20**	0.04
	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)
Tenure	0.02*	0.01	-0.04***	-0.04***	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Tenure squared	-0.04	-0.03	0.10***	0.09***	-0.04	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Demographic Variables						
Parent's education (base=neither of parents attained upper secondary)						
Secondary	0.03	-0.04	-0.18*	-0.14	-0.07	-0.06
	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)
Tertiary	0.29**	0.24*	-0.27*	-0.23*	-0.23*	-0.23*
	(0.10)	(0.10)	(0.11)	(0.10)	(0.11)	(0.10)
Male dummy	-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)
Occ. dummies	no	yes	no	yes	no	yes
Ind. and firm size d.	yes	yes	yes	yes	yes	yes
# of observations	1691	1691	1692	1692	1694	1694
Adjusted R-squared	0.282	0.355	0.279	0.344	0.185	0.326

Notes: All of the regressions are weighted with sampling weights. The significance is reported for the following levels: *** p<0.01; ** p<0.05; *p<0.1.

Interestingly, the parent's educational attainment is positively related to abstract task scores and negatively related to the routine and manual tasks scores. This highlights the implications of parent's transfer of social capital to their young.

Having no computer experience significantly affects all three task scores. Furthermore, the significance of the constant term for the routine tasks indicates that the specification needs to be better, and there are other factors significantly affecting the routine input that we do not include in the models.

We can draw a salient inference from Table 8: the task measures at the individual level yield a more pronounced influence on wage determination, than the task measures at the job level. We make this deduction from the observation that even when we control for the occupational dummies, the demographic variables maintain their statistical significance, except for the manual tasks. This conclusion favors task scores derived from PIAAC, as they provide worker-level information, as opposed to O*NET task scores aggregated at the occupational level.

Another critical implication we can draw from the results in Table 8 deserves attention. There are discernible variations in job tasks, which persist within specific occupations, differentiating workers based on their distinct human capital and demographic characteristics. This pattern alludes to a consequential implication. Considering the inherent correlations between job tasks and demographic variables, along with human capital and other occupations, job tasks must predict wages, given that these variables are in turn predictors of wages.

3.2 The Link Between Tasks and Wages

3.2.1 Descriptive Wage Regressions

To what degree does the variation self-reported job tasks within occupation is meaningful, in terms of making a substantial differences? To answer this question, we estimate the following Mincerian descriptive wage function by employing the PIAAC dataset:

$$W_i = a + \delta_A A_i + \delta_R R_i + \delta_M M_i + \delta_1 C_i + \delta_1 \mathbf{X_i} + \gamma_\mathbf{j} + \lambda_\mathbf{i} + \varepsilon_\mathbf{i} \tag{14}$$

Whereby, W_i is the wage decile of the worker i[7], while A_i, R_i, M_i denotes the

[7] A notable limitation of the PIAAC dataset is the absence of detailed earnings-related variables for certain countries, a gap attributed to data protection laws in some countries, including Turkey. Rather than containing precise earnings information, the dataset for these countries includes information that situates individuals within broad income categories. In fact, as reported by the OECD (2016), this shortcoming substantially mitigates the nonresponse rate, as respondents are allowed to denote their relative position within the broad income categories. Consequently, within the dataset, the variable denoting hourly income is represented in the form of ordinal numbers, signifying wage deciles. These deciles are derived from respondents' self-reported income responses, effectively capturing the distribution of earnings across the

abstract, routine and manual task inputs of worker i, respectively. The other parameters are the same in eq 13. The results are in Table 9.

As a benchmark, the first column in Table 9 presents a standard form of cross-sectional Mincerian wage regression of wages on human capital and demographic variables, along with industry and firm size dummies. The coefficients have signs and magnitudes, as expected. Column two, replaces demographic and human capital controls with task scores. Although the adjusted R-squared is 22.6%, the second model explains about 30% less wage variation than in the first column with only human capital and demographic measures.

In column 3, 2-digit occupation dummies performs slightly better (0.24) at predicting wages than the task scores in column 2. However, in column 4, in which the human capital and demographic measures control by the task measures, routine and manual tasks are no longer significant in the model. Interestingly, the task scores maintain their significance level if we add the controls of occupations in Column 6.

Task scores' significance in explaining wage variation disappears if we add the human capital and demographic controls. However, task scores maintain their significance when we control for the occupation dummies. This result indicates that the predictive power of task scores on wages almost entirely mediated by the demographic and human capital variables, except for the case of abstract tasks which maintains its significance level.

population.

Table 9: Estimation Results of the Descriptive Wage Function With Job Tasks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Task Categories							
Abstract		0.46***		0.23**		0.35***	0.26**
		(0.09)		(0.09)		(0.09)	(0.09)
Routine		-0.40***		-0.14		-0.28**	-0.10
		(0.09)		(0.09)		(0.09)	(0.09)
Manual		-0.30***		-0.11		-0.31***	-0.18*
		(0.07)		(0.07)		(0.08)	(0.07)
Education dummy (base=lower secondary or less)							
Upper secondary	0.82***			0.71***	0.59***		0.55**
	(0.16)			(0.16)	(0.17)		(0.17)
Tertiary 2-3 years	1.53***			1.27***	1.06***		0.90***
	(0.25)			(0.26)	(0.27)		(0.27)
Tertiary 4 years	3.12***			2.73***	2.39***		2.16***
	(0.23)			(0.25)	(0.28)		(0.28)
Tertiary Master	3.27***			2.71***	2.51***		2.11***
	(0.42)			(0.44)	(0.46)		(0.47)
No computer exp.	-0.36			-0.22	-0.28		-0.18
	(0.19)			(0.19)	(0.19)		(0.19)
Tenure	0.18***			0.16***	0.16***		0.15***
	(0.02)			(0.02)	(0.02)		(0.02)
Tenure squared	-0.41***			-0.39***	-0.38***		-0.36***
	(0.06)			(0.06)	(0.06)		(0.06)
Parent's education (base=neither of parents attained upper secondary)							
Secondary	0.14			0.11	0.10		0.11
	(0.22)			(0.22)	(0.23)		(0.23)
Tertiary	0.38			0.27	0.29		0.19
	(0.30)			(0.30)	(0.30)		(0.31)
Male dummy	-0.18			-0.12	-0.13		-0.07
	(0.16)			(0.16)	(0.16)		(0.16)
Age (5 year intervals)	0.11*			0.10*	0.15**		0.14**
	(0.05)			(0.05)	(0.05)		(0.05)
Constant	4.03***	6.02***	5.25**	4.25***	3.61***	9.65***	3.81***
	(0.65)	(0.60)	(1.78)	(0.65)	(0.86)	(2.17)	(0.86)
Occ. dummies	no	no	yes	no	yes	yes	yes
Ind. and firm size d.	yes	yes	yes	yes	yes	yes	yes
Observations	1522	1521	1527	1516	1522	1521	1516
Adjusted R-squared	0.319	0.226	0.247	0.328	0.338	0.277	0.346

Notes: All of the regressions are weighted with sampling weights. The significance is reported for the following levels: *** p<0.01; ** p<0.05; *p<0.1.

3.2.2 Testing Model's Predictions

To validate our approach, we first test the propositions in the previous section, by using the specification in Eq. 10. The theoretical framework of Autor and Handel (2013) anticipates that the point estimators for $\gamma_1, \ldots, \gamma_5$ would not uniformly display positive values. Similar to Autor and Handel (2013), the results presented in Table 10, display a notable presence of negative associations among task returns within occupations.

Table 10: Relationship Between the Coefficients Obtained from the Wage Function of Each Occupation

	b(man) (1)	b(abs) (2)	b(rou) (3)	Int (4)	Int (5)	Int (6)
b(abstract)	-0.33***			-0.16***		
	(0.00)			(0.00)		
b(routine)		0.94***			-0.10**	
		(0.00)			(0.00)	
b(manual)			-0.68***			0.29***
			(0.00)			(0.00)
Observations	2134	2134	2134	2134	2134	2134
Adjusted R-squared	0.229	0.622	0.309	0.013	0.003	0.019

Notes: All of the regressions are weighted with the sum of the workers in each occupation. Each column and each row corresponds to an individual OLS regression. Regressions involve the coefficient estimate against the coefficients listed in the table, along with a constant term. The dependent variables are from person-level wage regressions. The regressions consider standardized task input measures, and alongside an intercept term, are conducted distinctly within each 2-digit occupation category that comprises a minimum of five observations. p-values in parentheses. The significance is reported for the following levels: *** $p<0.01$; ** $p<0.05$; *$p<0.1$.

The second complementary framework of Roy model is the workers' ability to self-select into jobs. We test this implication by estimating the OLS regression in Eq. 12, from the previous section's second proposition. This model interacts with the self-reported task inputs with the average task input within the worker's occupation. Autor and Handel (2013) anticipates that, at least one of the interaction terms will be significantly positive. Table 11 shows the results.

Table 11: Wage Regressions with Interactions between Individual and Occupational Mean Task Use Intensity

	(1)	(2)	(3)	(4)	(5)	(6)
Task Categories (individual-level)						
Abstract	0.40***	0.37***	0.40***	0.36***	0.23**	0.26**
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Routine	-0.29**	-0.30**	-0.28**	-0.29***	0.00	0.0103
	(0.00)	(0.00)	(0.00)	(0.44)	(0.98)	(0.90)
Manual	-0.38***	-0.47***	-0.37***	-0.44***	-0.19***	-0.25
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Task Categories (occupational-level)						
Abstract	-0.11	-0.20	-0.17	-0.48	0.12	-0.034
	(0.71)	(0.62)	(0.65)	(0.20)	(0.74)	(0.93)
Routine	-1.23***	-1.17	-1.30***	-1.26***	-0.72*	-0.39
	(0.00)	(0.00)	(0.00)	(0.04)	(0.65)	(0.31)
Manual	0.14	0.04	0.13	0.18	0.58**	0.55**
	(0.45)	(0.83)	(0.48)	(0.31)	(0.00)	(0.00)
Abstract # abstract (mean)		0.03		-0.17		-0.067
		(0.86)		(0.25)		(0.63)
Routine # routine (mean)		0.10		-0.07		-0.12
		(0.53)		(0.65)		(0.40)
Manual # manual (mean)		-0.37**		-0.32**		-0.25*
		(0.01)		(0.14)		(0.04)
Gender and native language controls	No	No	Yes	Yes	Yes	Yes
Human capital and other controls	No	No	No	No	Yes	Yes
Observations	1527	1527	1527	1524	1522	1522
Adjusted R-squared	0.171	0.174	0.172	0.185	0.318	0.311

Notes: All of the regressions are weighted with sampling weights. p-values in parentheses. The significance is reported for the following levels: *** p<0.01; ** p<0.05; *p<0.1.

Table 11, column 1 presents the prior OLS model's extension with average task scores at the occupational level. Returns to tasks are significantly higher in abstract task intensive occupations and significantly lower in routine and manual intensive occupations. In the second column, individual level manual tasks' interaction with the occupation means is are significantly negative. Conversely, the other two interaction terms are nearly positive, but insignificant.

This outcome indicates contrary patterns to the Roy model, which posits expectations regarding the interaction terms. According to this model, at least one of the interaction terms' coefficient's should be positive and statistically significant. However, the findings we have obtained do not align with this proposition. This discrepancy prompts a thoughtful reflection on Proposition 2, which allows workers to exercise a degree of self-selection when choosing between different occupations. [8]

3.3 Explaining the Polarization

3.3.1 Polarization Tests

In this section, we first empirically test the employment and wage polarization since our previous preliminary exercises show potential signs of the routinization hypothesis of ALM. From 2004 to 2020, Turkey's labor market's share of routine jobs declined. This decline mostly comes from the manufacturing jobs and agricultural workers while the clerical jobs are more or less sustained their labor share. On the other hand, there is a substantial growth in the labor share of manual service jobs. In the meantime, there is a skill-biased change in mean wages in the first half of the study sample (2004-2012). However, in the latter period, the wage growths are mostly determined mainly by the minimum wage jumps starting from 2015. Stemming from the minimum wage increases, there is a decline in the premium of education, since minimum wage earners are mostly less educated and the real wage increases of university graduates are stagnant in this period.

The test for job polarization suggested by Goos and Manning (2007) is applied by several studies (Akçomak & Gürcihan, 2013; Marouani, Le, & Marshalian, 2020; Sebastian, 2018) to verify the routinization hypothesis. This test is structured upon the observation that the prevalence of routine intensities in middle-income jobs. As the routine task demand shrinks, there should be a decline in middle-income jobs which leads to a U-shaped pattern in the evolution of employment depicted in fig 6. This convex structure is tested with the following specification:

$$\Delta log n_j = \beta_0 + \beta_1 log(w_{j0}) + \beta_2 log(w_{j0})^2, \qquad (15)$$

Goos and Manning (2007) predicted the linear term $\beta_1 w_{j0}$ negative and the

[8] We test the proposition with the O*NET data, which have occupation level measures. We substituted the O*NET task scores with PIAAC occupational level task scores (based on our calculation). The outcome of this substitution, however, yields results that align closely with the original findings.

quadratic term $\beta_2 w_{j0}$ positive in the above equation, whereby $\Delta logn_j$ is the change in log employment share in job j and w_{j0} is the initial log median wage in job j. If the β_1 and β_2 are significantly negative and positive, respectively, there is a pattern of polarization.

Hollowing out of middle-skill jobs is also causing middle-skill real wages to decline because of the relative demand shortage these occupations experience. Therefore, in the presence of job a significantly negative β_1 and a significantly negative β_2 we should also see a U-shaped pattern in the change of log mean earnings. Therefore, Sebastian (2018) proposed the following specification to test the relationship between the initial wages and wage growths in the occupations:

$$\Delta logw_j = \beta_0 + \beta_1 log(w_{j0}) + \beta_2 log(w_{j0})^2, \qquad (16)$$

where $\Delta logw_j$ is the change in the log mean wage of job j in the time period, and the other parameters are the same as in equation 15. Table 12 reports the estimation results of equation 15 and equation 16.

Table 12: Polarization Tests for Jobs and Earnings

	Δ in employment share		Δ in log mean real wage	
	2004/12	2012/22	2004/12	2012/22
	(1)	(2)	(3)	(4)
Initial log mean wage	-3.24	-3.35	-9.44**	-0.68
	(0.33)	(0.25)	(0.00)	(0.58)
Sq. initial log mean wage	0.27	0.25	0.72**	0.03
	(0.29)	(0.22)	(0.00)	(0.71)
Constant	9.65	10.97	31.31**	3.28
	(0.37)	(0.29)	(0.00)	(0.45)
Observations	22	32	22	32
R^2	0.295	0.259	0.423	0.624
Adj. R^2	0.221	0.208	0.362	0.598

Notes: Standard errors are in parentheses. The significance is reported for the following levels: *** p<0.01; ** p<0.05; *p<0.1.

In the next step, we estimate the models presented in Table 12 using O*NET data. The specification as follows:

$$\Delta logn_j = \beta_0 + \beta_1 RTI_{j,t-1}, \qquad (17)$$

$$\Delta log n_j = \beta_0 + \beta_1 RTI_{j,t-1} + \beta_1 RTI^2_{j,t-1}, \tag{18}$$

$$\Delta log w_j = \beta_0 + \beta_1 RTI_{j,t-1}, \tag{19}$$

$$\Delta log w_j = \beta_0 + \beta_1 RTI_{j,t-1} + \beta_1 RTI^2_{j,t-1}. \tag{20}$$

In each equation, we apply the specifications defined in 15 , and Eq. 16, utilizing the occupational-level RTI index to explore the relationship between RTI and the two primary labor market dynamics: wage and employment changes. Table 13 displays the results. Although the R-squared values are slightly higher in estimations utilizing the O*NET data, the point estimates are generally insignificant. However, the O*NET data outperforms the PIAAC data slightly in explaining the variance in employment and wage changes. While the significance level is modest (5% statistical significance), the coefficients in the linear terms are negative for the initial period. This implies a negative relationship between routine intensity and both the occupation's wage and employment share.

Considering the estimations of linear specifications in Eq. 17 and Eq. 19, the linear terms of O*NET measures are negatively significant for the first period in both employment change and wage change. However, the point estimates are only significant at the 5% statistical significance level. In the second period, the relationship turns positive and becomes significant for wage change. The results are presented in Appendix Table A6.

Table 13: Estimations of Quadratic Relationship Between RTI Measures and Employment Dynamics

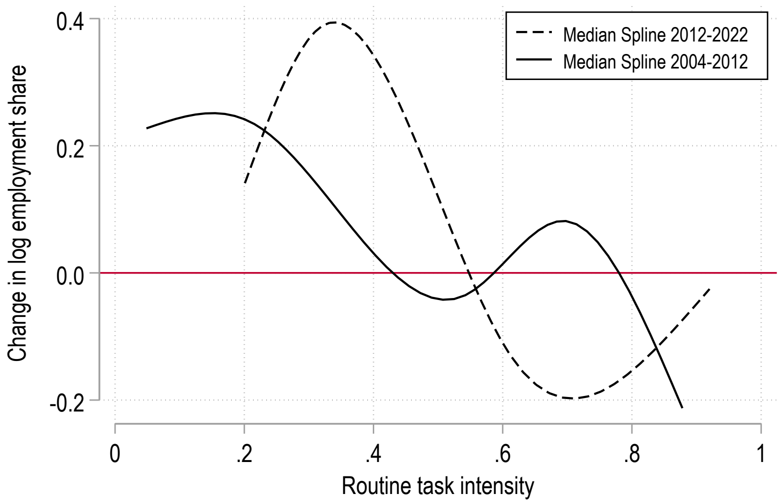
	Δ in employment share		Δ in log mean real wage	
	2004/12	2012/22	2004/12	2012/22
	(1)	(2)	(3)	(4)
Panel A. Occupation level routine task intensities from PIAAC data				
RTI (PIAAC)	0.01	-0.06	-0.10	0.67*
	(0.93)	(0.92)	(0.10)	(0.04)
Sq. RTI (PIAAC)	0.05	-0.09	-0.03	-0.47
	(0.35)	(0.88)	(0.49)	(0.16)
Constant	-0.02	0.02	0.43***	-0.06
	(0.67)	(0.89)	(0.00)	(0.40)
Observations	22	32	22	3a2
R^2	0.051	0.026	0.138	0.242
Adj. R^2	-0.048	-0.041	0.047	0.190
*Panel B. Occupation level routine task intensities from O*NET data*				
RTI (O*NET)	-0.06*	-0.95	-0.05*	0.49
	(0.02)	(0.15)	(0.04)	(0.12)
Sq. RTI (O*NET)	-0.00	0.65	-0.00	-0.17
	(0.80)	(0.22)	(0.76)	(0.50)
Constant	0.01	0.26	0.42***	-0.10
	(0.79)	(0.15)	(0.00)	(0.24)
Observations	22	32	22	32
R^2	0.273	0.098	0.198	0.412
Adj. R^2	0.197	0.036	0.114	0.372

Notes: The RTI measures are obtained from the occupation level aggregation of individual level PIAAC task measures, and O*NET data. p-values in parentheses. The significance is reported for the following levels: *** p<0.01; ** p<0.05; *p<0.1.

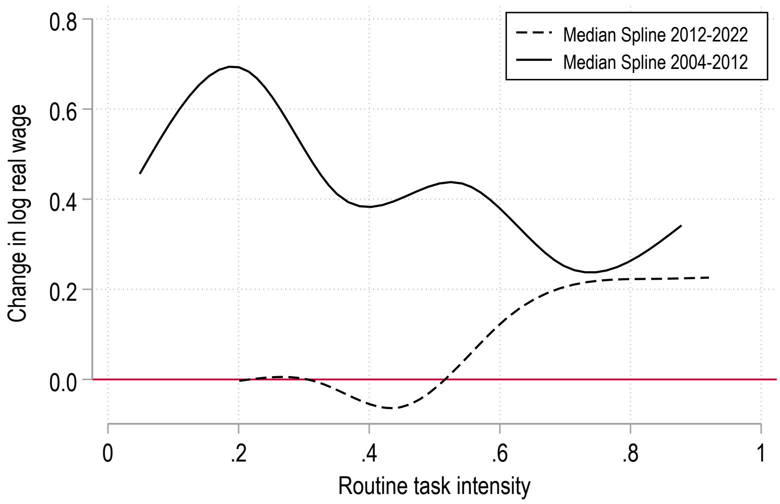
Figure 10 visualizes the results in Table 13. Since the quadratic fits have no significance level, Figure 10 plots the median splines. [9]

[9] Median splines provide a flexible approach for capturing nonlinear relationships between covariates. They offer increased robustness in estimating trends, particularly with respect to their sensitivity to outliers, when compared to quadratic and linear fits. Given our objective of visualizing trends while maintaining sensitivity to observed values, and considering that our attempts at quadratic estimations did not yield significant results, median splines emerge as a more robust visualization option

Figure 10: Wage and Employment Change Over RTI



(a) Effect of RTI on Change in Employment Shares



(b) Effect of RTI on Change in Log Real Wages

Notes: Point estimates from Graph 6 calibrated with the occupation-specific routine task intensities from O*NET data.

3.3.2 Occupations' Role in Explaining Wage Polarization

In order to identify the role of occupations in explaining wage differentials, we followed the approach of Firpo et al. (2011); Fortin and Lemieux (2016). First, we created a dataset consisting 9 deciles of wages for each occupation for the years of 2004, 2012 and 2022, separately, w^q_{jt} for q = 10, 20, ... 90. Therefore, we created a dataset of 225 observations for 25 occupation category and 9 deciles. Fortin, Lemieux, and Firpo (2011) estimated the following model to measure wage differences between years at wage deciles:

$$\Delta w_j^q \quad = \quad \widetilde{a_j} + \widetilde{b_j} w_{j0}^q + \lambda^q + \varepsilon_j^q, \tag{21}$$

Whereby, w denotes wage, j is occupation, $q$is the decile, and w_0 stands for the base wage. The error term of the model is the compound of decile-specific error component, λ^q, which measures the change in return to unobservable skills[10], and idiosyncratic error term, ε_j^q, which we assume to be normally distributed. In this model, the parameter $\tilde{a_j}$ is the occupation-specific constant, and $\tilde{b_j}$ is the occupation-specific slope. When the Eq. 21 estimated, the intercept $\tilde{a_j}$ captures between-occupation changes in wage dispersion and $\tilde{b_j}$ captures the within-occupation changes. In the second step of the analysis, they link the estimated intercepts and slopes ($\tilde{a_j}$ and $\tilde{b_j}$) to the measures of task content of occupations to analyze the effect of technology and offshoring. Specifically, they used a task-occupation dataset to see how well the task measures explains the intercepts and slopes.

In Figure 11 we plot the real wage changes of each period by using the raw data used in the estimation in Table 14 (N=255). The figure plots the 255 observed wage changes as a function of the base wages. In the first period, wage data yields a U-shaped pattern, which is well-known in the related literature. In the second period, the curvature weakens. The empirical strategy of the first stage analysis in Table 14, attempts to see the explanatory power of the simple linear model in eq 21 on explaining the variation reported in Figure 11. Moreover, we report the regression results to determine the exact value of the curvature in Figure 11 below:

$$\widehat{\Delta wage} \quad = \underset{(0.103)^{***}}{-0.978} logwage(2004) + \underset{(.019)^{***}}{.175} logwage(2004)^2 + \underset{(0.135)^{***}}{1.548}, \tag{22}$$

The standard error values in this model indicate that the coefficients are statistically significant at the 1% significance level. Quadratic form coefficient (π_2 in eq 23) implies that there is a statistically significant convexity in the wage differences in the period of 20004 to 2012.

[10]For example, if the unobservable skills in the regression, such as the unmeasured school quality, changes in the returns to school quality will be captured by the error component λ^q if it is equally distributed and rewarded across all occupations.

Figure 11: Changes in Real Log Wages by Decile

(a) 2004-2012

(b) 2012-2020

Notes: Each point represents a decile for each occupation and diameters are adjusted according to labor supply weight of each plotted point.

Following Firpo et al. (2011), we estimated several versions of Eq. 21, which are reported in Table 14. To evaluate the empirical performance of the models, we use two measures. Firstly, the adjusted R-square values for each model are evaluated to determine the extent to which the model performs in predicting wages. However, due to the residual sampling error, Firpo et al. (2011) denote that the wage change estimation does not explain all the variation in the data.

The second measure of fit relies on the performance of each model in explaining the curvature in Figure 11. For each model, we run a quadratic regression of the residuals estimated in the model on a linear and quadratic term in the base wage to see the amount of decrease in the curvature, by using the following specification:

$$\hat{\varepsilon_j^q} = \pi_0 + \pi_1 w_{j0}^q + \pi_2 (w_{j0}^q)^2 + \upsilon_j^q, \tag{23}$$

As a reference, quadratic term coefficient ($\hat{\pi_2}$) from the fitted regression of the raw data is 0.175 which is reported in eq 22. In the first model of Table 14 (column 1), eq 21 is estimated as a benchmark, having only the base wage as an explanatory variable. Adjusted R-square (0.027) shows that the explained variation in the data is negligible. As expected, the linear model can not explain the curvature of the changes in wages; thus, the curvature parameter in the residuals from this model is close to 22.

Table 14: Regression Fit of Models for Changes in Wages at Each Decile, by Two-Digit Occupation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Occupation dummies		X		X	X	X	X
Decile dummies			X	X	X		X
Base wage	X				X	X	X
Occupation*base wage (slope)					X	X	
Adj. R^2	0.027	0.420	0.108	0.560	0.821	0.808	0.601
Curvature in resid. (β_2)	0.193***	0.120***	0.186***	0.113***	0.0167	0.028**	0.091***
(N=225)	(0.017)	(0.012)	(0.017)	(0.012)	(0.008)	(0.009)	(0.012)

Notes: Regressions are estimated for each decile within each occupation category. The independent variable is the wage changes between years, represented as the difference between the logarithm of wages for t $log(w_t)$ and the logarithm of the wages at the base year $log(w_0)$. The analysis includes a total of 255 observations, encompassing 25 occupations and 9 deciles for each occupation. To account for the varying representation of occupations in the labor market, the models are weighted by the labor supply allocated to each occupation category in the base year, calculated as the product of usual weekly working hours and the corresponding sampling weight for each observation. Standard errors are in parentheses. *** p<0.01; ** p<0.05; *p<0.1.

If we only include the set of occupation dummies (the $\widetilde{a_j}'$s) in the model, as in model 2, it explains 42% of the raw variation in the data. Model 2 also explains about a two third of the curvature, which we see from the curvature parameter declining from 0.193 to 0.120, although it is still significant at the 1 percent significance level. Since we did not include any other variable in Model 2, it restricts of the same rate of increase in the wage deciles within a given occupation category. This assumption relates to the case that there is no within-occupation wage inequality.

In model 3, we only include the decile dummies (λ^q's). The explanatory power of the model is too little (0.108), likewise the residuals only explain a 3 percent of the curvature. This result implies that the within-occupation change in wage inequality does not explain the observed change in wages. In model 4, occupation dummies and decile dummies are combined. The adjusted R^2 (0.560) indicates that occupation-specific factors could explain the substantial portion of within-occupation changes in the wage distribution. We can make this inference by comparing the adjusted R-square values of model 4 and model 2. Since adding the decile dummies to Model 2 improves the explanatory power only marginally, we can interpret this as the increase in returns to skill has little impact on explaining variations in wage levels within occupations. Thus, occupation-specific factors has more effect on within-occupation wage dispersion.

The fit of the model improves substantially to 0.821 in Model 5, once we introduced occupation-specific slopes ($\widetilde{b_j}$'s). More importantly, the curvature parameter is no longer statistically significant (0.0167). In other words, by using occupation-specific slope, we can explain the wage polarization in the sample data. When we compare the adjusted R-squared of Model 6 and Model 7, we see that the occupation interactions have made significant impacted, rather than decile dummies.

When contrasting the curvature between Model 2 and Model 7, considering their minimal disparity, we can infer that the wage inequality observed during the initial study period finds its primary explanation in the occupation-specific variables. This observation underscores the significant role played by these variables in clarifying the wage dynamics within the studied period. Moreover, the result highlights the superiority of individual-level task data from PIAAC in explaining wage dispersions, rather than relying on occupation-level O*NET data.

4 CONCLUDING REMARKS

This thesis examines the Turkey's labor market dynamics over the past two decades, leveraging the comprehensive micro data provided by TurkStat. The primary focus of this study is to unravel and analyze the intricate interplay surrounding the phenomenon of job polarization within the Turkish context. Through the utilization of both descriptive and empirical analyses, a multitude of noteworthy observations come to the fore, demanding comprehensive examination.

Firstly, a pivotal observation emerges with the stagnation in real wage growth for the high-skilled segment of the Turkish workforce after the year 2016. This intriguing pattern diverges from the conventional trajectory, wherein technological advancements typically augment the skill premium. The necessity to investigate to what extent the pattern in Turkey's labor market is attributed to the minimum wage hikes becomes evident.

Secondly, a distinct polarization pattern becomes evident during the latter decade of the analyzed dataset, encompassing the most recent ten years. This pattern manifests as employment growth at the tail of the wage distribution and a systematic decline in employment within the middle range. This structural phenomenon warrants particular attention within the context of this study, prompting a comprehensive exploration to uncover the underlying drivers of this polarization pattern.

In pursuit of explanatory insights, firstly, this study employs a shift-share analysis. This analytical approach is wielded to dissect the shifts in employment dynamics across various sectors. One prominent insight derived from this examination is the role of the transition from the manufacturing sector to the service sector. This transition contributes partially to the observed polarization pattern. Specifically, as employment migrates from manufacturing to the service sector, it appears to be channeled into both the low-skilled service segment, characterized by inherent pressures, as well as the high-skilled segment.

In conclusion, this investigation provides valuable insights into Turkey's labor market dynamics, particularly within the context of job polarization. The observed wage stagnation among highly skilled workers and the polarized employment growth patterns necessitate a nuanced understanding of the intricate forces at play. By shedding light on the interplay between sectoral shifts, employment dynamics, and wage distribution, this study contributes to the broader discourse surrounding labor market transformations and contributes with the evidence from Turkey.

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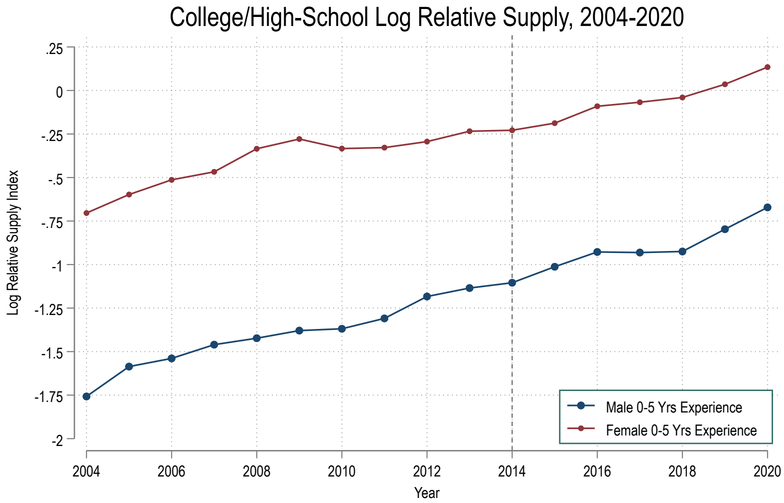
Apendix

Figure 12: Task Components

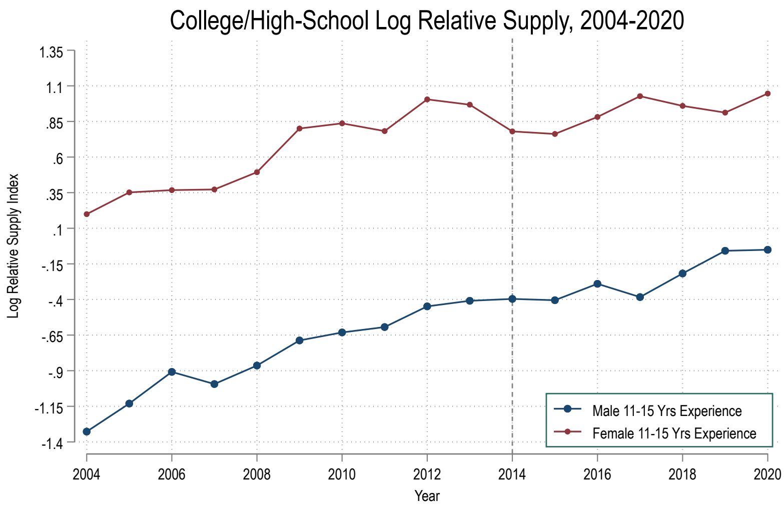
Variable	DOT definition	Task interpretation	Example tasks from *Handbook for Analyzing Jobs*
1. GED Math (MATH)	General educational development, mathematics	Measure of nonroutine analytic tasks	Lowest level: Adds and subtracts 2-digit numbers; performs operations with units such as cup, pint, and quart. Midlevel: Computes discount, interest, profit, and loss; inspects flat glass and compiles defect data based on samples to determine variances from acceptable quality limits. Highest level: Conducts and oversees analyses of aerodynamic and thermodynamic systems . . . to determine suitability of design for aircraft and missiles.
2. Direction, Control, Planning (DCP)	Adaptability to accepting responsibility for the direction, control, or planning of an activity	Measure of nonroutine interactive tasks	Plans and designs private residences, office buildings, factories, and other structures; applies principles of accounting to install and maintain operation of general accounting system; conducts prosecution in court proceedings . . . gathers and analyzes evidence, reviews pertinent decisions . . . appears against accused in court of law; commands fishing vessel crew engaged in catching fish and other marine life.
3. Set Limits, Tolerances, or Standards (STS)	Adaptability to situations requiring the precise attainment of set limits, tolerances, or standards	Measure of routine cognitive tasks	Operates a billing machine to transcribe from office records data; calculates degrees, minutes, and second of latitude and longitude, using standard navigation aids; measures dimensions of bottle, using gauges and micrometers to verify that setup of bottle-making conforms to manufacturing specifications; prepares and verifies voter lists from official registration records.
4. Finger Dexterity (FINGDEX)	Ability to move fingers, and manipulate small objects with fingers, rapidly or accurately	Measure of routine manual tasks	Mixes and bakes ingredients according to recipes; sews fasteners and decorative trimmings to articles; feeds tungsten filament wire coils into machine that mounts them to stems in electric light bulbs; operates tabulating machine that processes data from tabulating cards into printed records; packs agricultural produce such as bulbs, fruits, nuts, eggs, and vegetables for storage or shipment; attaches hands to faces of watches.
5. Eye Hand Foot Coordination (EYEHAND)	Ability to move the hand and foot coordinately with each other in accordance with visual stimuli	Measure of nonroutine manual tasks	Lowest level: Tends machine that crimps eyelets, grommets; next level: attends to beef cattle on stock ranch; drives bus to transport passengers; next level: pilots airplane to transport passengers; prunes and treats ornamental and shade trees; highest level: performs gymnastic feats of skill and balance.

Source: Appendix of Autor et al. (2003).

Figure 13: College/High-School Dynamics and Experience Interactions



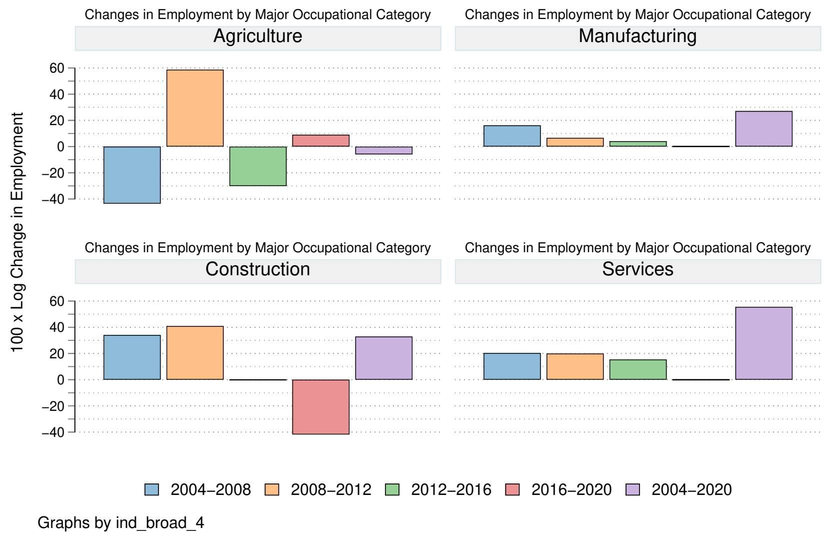
(a) College/High-School Log Relative Supply, 2004-2020 (0-5 Years of Experience)



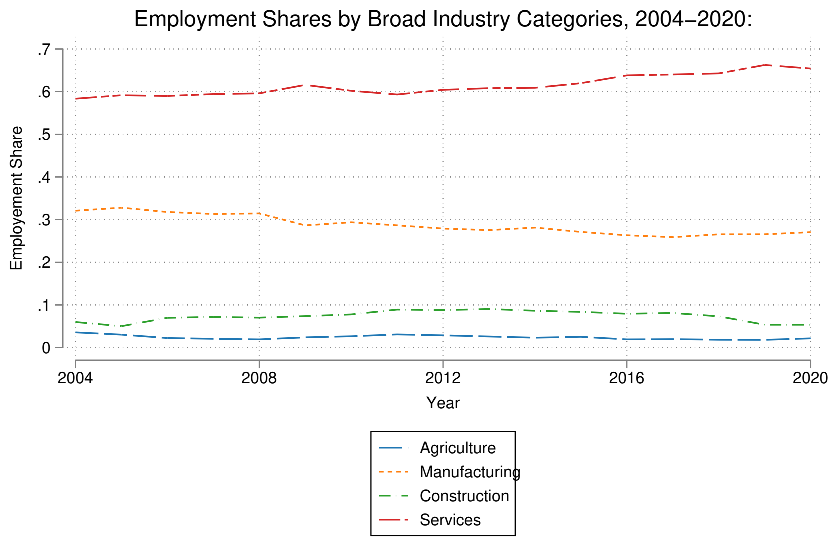
(b) College/High-School Log Relative Supply, 2004-2020 (11-15 Years of Experience)

Source: Author's calculations based on HLFS using efficiency units. The log relative supply of females and males from different experience levels.

Figure 14: Employment Changes Across Major Industry Categories



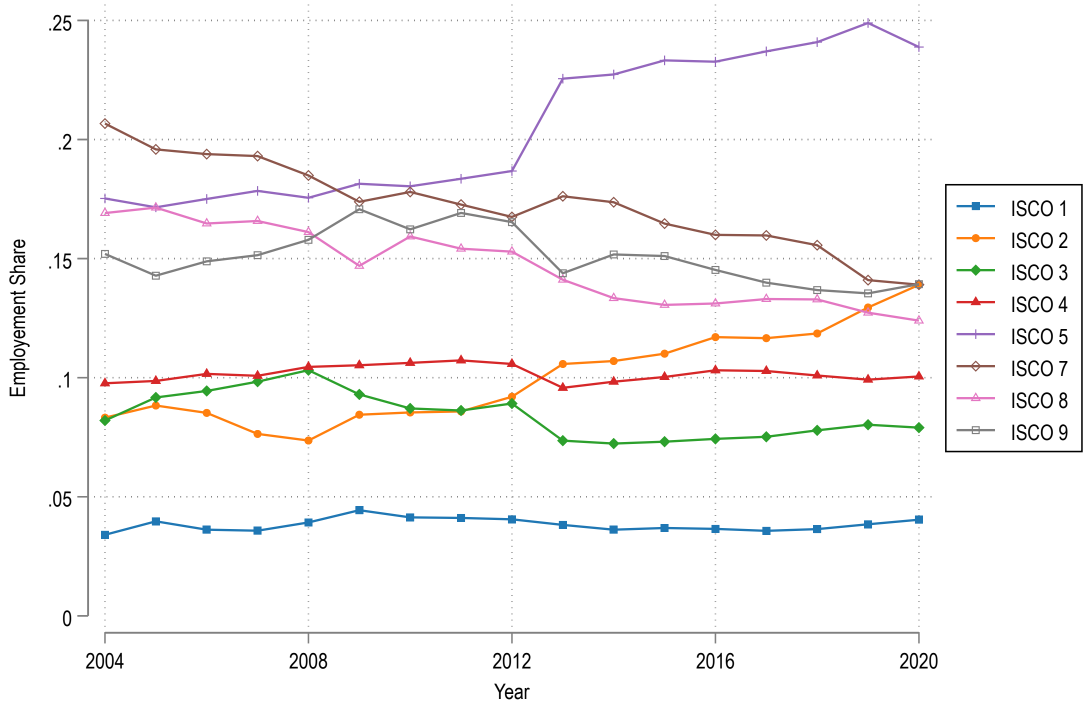
(a) Bar Plots



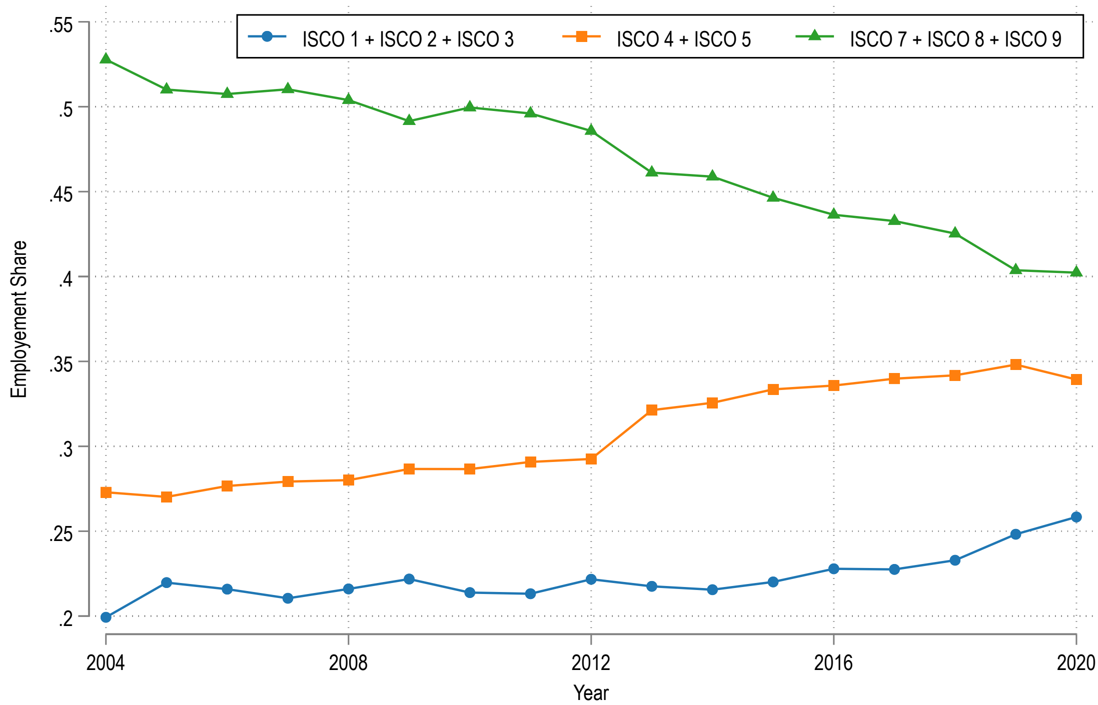
(b) Time Series Plot

Source: Author's calculations based on the corresponding waves of HLFS.

Figure 15: Employment Shares of Major Occupational Groups



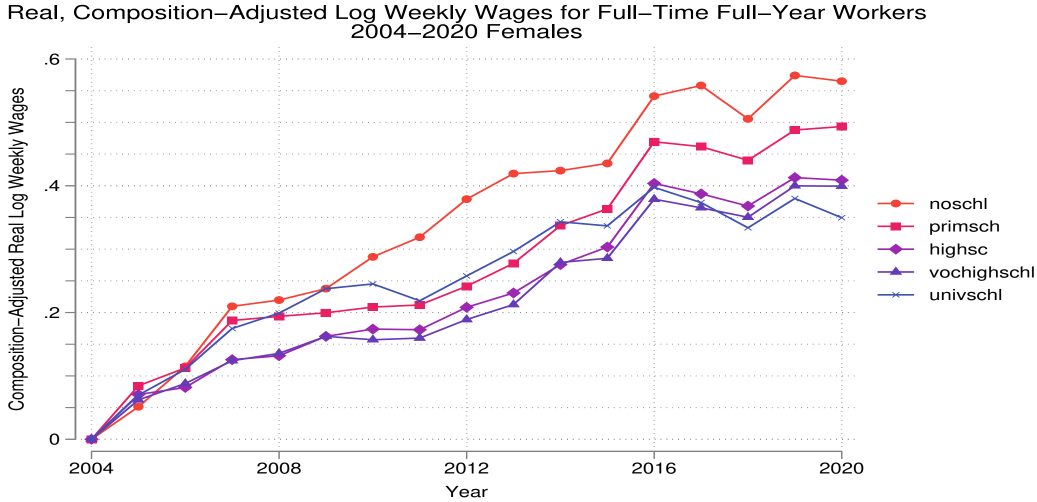
(a) Employment Shares by 1-digit ISCO Occupation Classifications



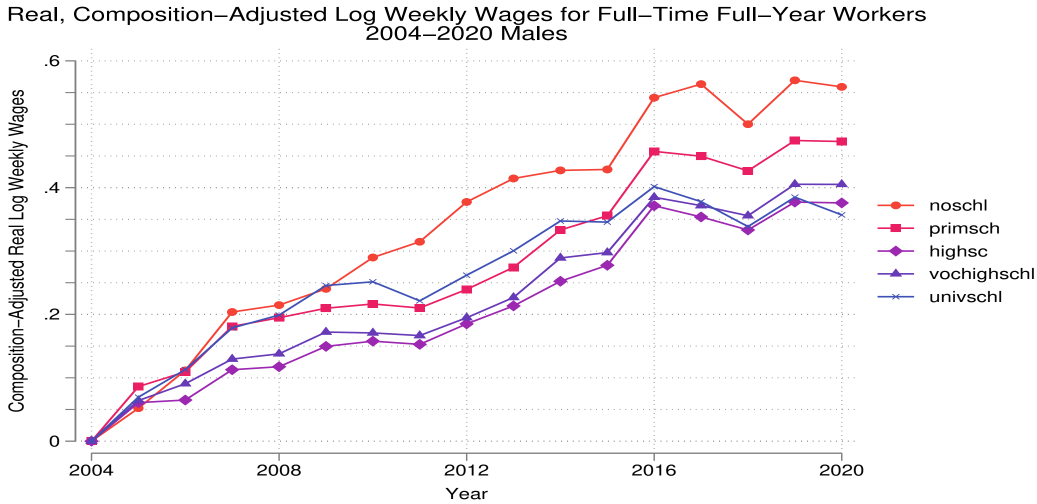
(b) Employment Shares by Broad Major Occupatinoal Groups

Notes: Author's calculations based on the corresponding waves of HLFS.

Figure 16: Composition Adjusted Log Real Wages of Education Cohorts



(a) Females Sample



(b) Males Sample

Source: Authors's calculatiions using HLFS (2004-2020). Calculation of the labor supply is based on the reported usual weekly working hours of all persons aged 14-64 who are employed and either revieving a monthly wage or a salary. The real log weekly wages for each education category is the weighted average of the relevant composition adjusted cells using a fixed set of weights equal to the average employment share of each group. Predicted nominal wages are deflated by the GDP deflator. (noschl: below primary school, primsch: primary school, highsc: high school, vochighschl: vocational high school, univschl: college)

Figure 17: Cross-sectional Relationship Between Mean Wages and Task Importance Measures

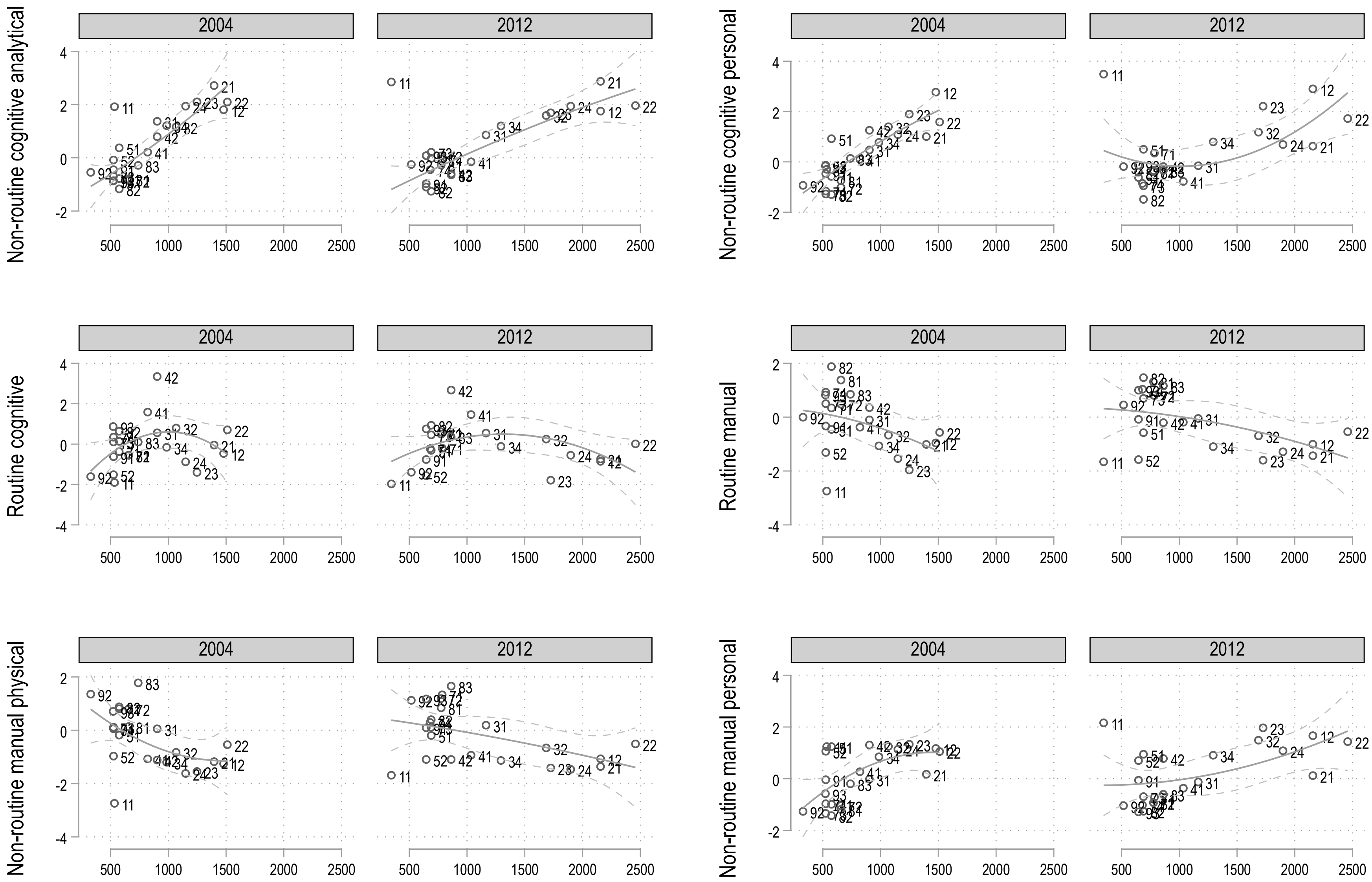


Figure 18: Country Specific Tasks

Skill Categories	**2- digit occupa-tions**	**Non-routine cognitive analytical**	**Non-routine cognitive personal**	**Routine Cognitive**	**Routine Task Index**
Skilled	11	0.11	0.01	-0.47	-0.43
Skilled	12	0.55	0.01	0.00	-0.31
Skilled	13	-0.29	0.21	0.23	0.28
Skilled	14	0.04	-0.49	0.07	0.28
Skilled	21	0.62	0.34	0.36	-0.16
Skilled	22	0.00	0.12	0.43	0.30
Skilled	23	0.62	1.31	0.34	-0.52
Skilled	25	1.17	0.88	-0.23	-1.03
Skilled	26	0.44	1.29	-0.01	-0.67
Skilled	31	-0.22	-0.32	0.10	0.31
Skilled	32	0.03	-0.12	0.15	0.18
Skilled	33	-0.19	-0.24	0.08	0.29
Skilled	34	-0.05	0.44	-0.47	-0.43
Skilled	35	1.33	-0.05	-0.05	-0.79
Semi-skilled w.c	41	-0.02	0.25	0.21	0.10
Semi-skilled w.c	42	0.17	-0.28	0.11	0.05
Semi-skilled w.c	43	-0.07	-0.26	0.13	0.30
Semi-skilled w.c	44	0.42	-0.34	-0.95	-0.94
Semi-skilled w.c	51	-0.24	-0.35	-0.31	0.02
Semi-skilled w.c	52	-0.18	-0.13	-0.36	-0.13
Semi-skilled w.c	53	-0.58	-0.14	-0.68	-0.15
Semi-skilled w.c	54	-0.12	0.19	0.25	0.20
Semi-skilled b.c	61	-0.37	-0.36	-0.27	0.12
Semi-skilled b.c	62	-0.82	-0.64	-0.43	0.44
Semi-skilled b.c	63	0.42	1.60	-0.95	-1.51
Semi-skilled b.c	71	-0.18	-0.34	-0.22	0.06
Semi-skilled b.c	72	-0.09	-0.45	0.02	0.21
Semi-skilled b.c	73	-0.45	0.02	-0.02	0.22
Semi-skilled b.c	74	0.17	-0.10	-0.31	-0.33
Semi-skilled b.c	75	0.07	-0.21	0.01	0.01
Semi-skilled b.c	81	-0.36	-0.32	0.30	0.51
Semi-skilled b.c	82	-0.09	-0.63	0.86	0.83
Semi-skilled b.c	83	-0.02	-0.18	0.23	0.22
Elementary	91	0.33	-0.52	-0.24	-0.21
Elementary	92	-0.29	-0.15	-0.52	-0.19
Elementary	93	-0.26	-0.13	0.31	0.42
Elementary	94	-0.05	-0.70	-0.31	0.02
Elementary	95	0.48	-0.34	-0.95	-0.91
Elementary	96	-0.48	-0.28	0.14	0.49

Notes: Author's calculations based on PIAAC data.

Table A1: ISCO08 Occupational Codings

International Standard Classification of Occupations (ISCO 08)

Code	Description
11	Chief executives, senior officials and legislators
12	Administrative and commercial managers
13	Production and specialised services managers
14	Hospitality, retail and other services managers
21	Science and engineering professionals
22	Health professionals
23	Teaching professionals
24	Business and administration professionals
25	Information and communications technology professionals
26	Legal, social and cultural professionals
31	Science and engineering associate professionals
32	Health associate professionals
33	Business and administration associate professionals
34	Legal, social, cultural and related associate professionals
35	Information and communications technicians
41	General and keyboard clerks
42	Customer services clerks
43	Numerical and material recording clerks
44	Other clerical support workers
51	Personal service workers
52	Sales workers
53	Personal care workers
54	Protective services workers
61	Market-oriented skilled agricultural workers
62	Market-oriented skilled forestry, fishery and hunting workers
63	Subsistence farmers, fishers, hunters and gatherers
71	Building and related trades workers, excluding electricians
72	Metal, machinery and related trades workers
73	Handicraft and printing workers
74	Electrical and electronic trades workers
75	Food processing, wood working, garment and other craft and related trades workers
81	Stationary plant and machine operators
82	Assemblers
83	Drivers and mobile plant operators
91	Cleaners and helpers
92	Agricultural, forestry and fishery labourers
93	Labourers in mining, construction, manufacturing and transport
94	Food preparation assistants
95	Street and related sales and service workers
96	Refuse workers and other elementary workers

Source: TurkStat

Table A2: ISCO88 Occupational Codings

International Standard Classification of Occupations (ISCO 88)

Code	Description
11	Legislators and senior officials
12	Corporate managers
13	Managers of small enterprises
21	Physical, mathematical and engineering science professionals
22	Life science and health professionals
23	Teaching professionals
24	Other professionals
31	Physical and engineering science associate professionals
32	Life science and health associate professionals
33	Teaching associate professionals
34	Other associate professionals
41	Office clerks
42	Customer services clerks
51	Personal and protective services workers
52	Models, salespersons and demonstrators
61	Market-oriented Skilled agricultural and fishery workers
62	Subsistence agricultural and fishery workers
71	Extraction and building trades workers
72	Metal, machinery and related trades workers
73	Precision, handicraft, craft printing and related trades workers
74	Other craft and related trades workers
81	Stationary plant and related operators
82	Machine operators and assemblers
83	Drivers and mobile plant operators
91	Sales and services elementary occupations
92	Agricultural, fishery and related labourers
93	Labourers in mining, construction, manufacturing and transport

Source: TurkStat

Table A3: Means of O*NET task measures for four broad occupational groups in 2015

	All	Below Primary	Primary	High School	Voc. High School	College
A. Females						
Non-routine cognitive						
Non-routine cognitive analytical	0.12	-0.45	-0.60	-0.26	-0.03	1.08
Non-routine cognitive personal	0.11	-0.23	-0.42	-0.15	-0.03	0.82
Non-routine manual						
Non-routine manual physical	-0.48	0.12	0.09	-0.54	-0.51	-1.12
Non-routine manual personal	0.27	-0.04	-0.31	0.13	0.28	0.94
Routine						
Routine cognitive	-0.15	-0.72	-0.28	0.34	0.35	-0.25
Routine manual	-0.36	0.08	0.23	-0.33	-0.33	-1.03
Routine task intensity	-0.18	-0.16	0.24	0.30	0.17	-0.85
B. Males						
Non-routine cognitive						
Non-routine cognitive analytical	-0.04	-0.46	-0.43	-0.11	-0.05	1.02
Non-routine cognitive personal	-0.04	-0.37	-0.36	0.005	-0.11	0.80
Non-routine manual						
Non-routine manual physical	0.17	0.63	0.56	0.02	0.19	-0.78
Non-routine manual personal	-0.09	-0.59	-0.45	0.06	-0.12	0.76
Routine						
Routine cognitive	0.05	-0.20	0.04	0.25	0.32	-0.15
Routine manual	0.12	0.57	0.51	-0.04	0.16	-0.82
Routine task intensity	0.06	0.22	0.33	0.16	0.21	-0.75

Source: Author's calculations based on the framework introduced by Acemoglu and Autor (2011).

Table A4: Occupation's Rank by RTI Index (2004)

Occupation	RTI	Weekly Wage	Level	Cumulative	Top 33%
82	1.60	2.48	9.05	9.05	X
74	1.41	2.32	7.52	16.57	X
81	1.21	2.53	1.37	17.94	X
73	1.16	2.50	1.13	19.07	X
41	0.78	2.85	7.62	26.69	X
72	0.55	2.65	5.95	32.64	X
42	0.46	2.92	2.63	35.27	X
93	0.25	2.36	4.05	39.32	
71	0.15	2.49	5.53	44.85	
91	0.03	2.41	7.36	52.21	
52	-0.21	2.26	6.29	58.50	
61	-0.25	2.36	0.51	59.01	
34	-0.36	3.02	4.32	63.33	
24	-0.61	3.21	2.50	65.83	
32	-0.71	3.15	1.43	67.26	
51	-0.79	2.55	10.43	77.69	
13	-0.81	2.64	1.04	78.74	
21	-0.86	3.40	1.25	79.99	
31	-0.87	2.98	3.04	83.02	
83	-0.91	2.57	8.25	91.27	
92	-1.13	2.13	1.34	92.62	
12	-1.18	3.44	2.55	95.17	
22	-1.27	3.54	0.86	96.03	
23	-2.27	3.53	3.97	100.00	

Source: Author's calculations using HLFS.

Table A5: Task Importance Measures

ISCO	NRCA	NRCP	RCOG	RMAN	NRMPHYS	NRMPERS
11	1.92	-0.30	-1.90	-2.74	-2.74	1.24
12	1.80	2.77	-0.47	-0.96	-1.26	1.17
21	2.71	1.00	-0.05	-1.01	-1.18	0.17
22	2.09	1.58	0.70	-0.57	-0.54	1.05
23	2.10	1.90	-1.40	-1.96	-1.55	1.33
24	1.94	1.08	-0.88	-1.54	-1.62	1.14
31	1.37	0.47	0.56	-0.10	0.06	-0.02
32	1.16	1.40	0.79	-0.67	-0.83	1.25
34	1.21	0.77	-0.16	-1.07	-1.20	0.85
41	0.21	0.10	1.58	-0.37	-1.07	0.27
42	0.79	1.26	3.34	0.35	-1.12	1.30
51	0.37	0.92	0.14	-0.46	-0.18	1.24
52	-0.08	-0.13	-1.51	-1.31	-0.97	1.06
71	-0.78	-0.58	-0.37	0.34	0.81	-0.99
72	-0.85	-1.02	-0.55	0.49	0.81	-1.05
73	-0.69	-1.27	0.11	0.50	0.11	-1.34
74	-0.86	-1.16	0.34	0.93	0.08	-0.97
81	-0.80	-0.75	-0.55	1.38	0.14	-1.19
82	-1.17	-1.30	0.64	1.88	0.88	-1.43
83	-0.29	0.14	0.10	0.85	1.78	-0.19
91	-0.45	-0.47	-0.62	-0.33	0.06	-0.04
92	-0.55	-0.93	-1.61	0.00	1.35	-1.26
93	-0.87	-0.16	0.87	0.82	0.71	-0.58

Source: Author's calculations using HLFS.

Table A6: Polarization Tests for Jobs and Earnings

	Δ in employment share		Δ in log mean real wage		Δ in employment share		Δ in log mean real wage	
	2004/12	2012/22	2004/12	2012/22	2004/12	2012/22	2004/12	2012/22
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RTI (O*NET)	-0.06*	-0.17	-0.05*	0.29***				
	(-2.73)	(-1.26)	(-2.20)	(4.50)				
RTI (PIAAC)					-0.02	-0.14	-0.08	0.23*
					(-0.35)	(-0.88)	(-1.61)	(2.63)
Constant	0.00	0.08	0.41***	-0.05	0.01	0.04	0.41***	0.02
	(0.14)	(0.77)	(12.09)	(-1.16)	(0.16)	(0.39)	(11.63)	(0.35)
Observations	22	32	22	32	22	32	22	32
R-squared	0.271	0.050	0.194	0.403	0.006	0.025	0.115	0.187
Adjusted R-squared	0.234	0.018	0.154	0.383	-0.044	-0.007	0.071	0.160

Notes: t statistics in parentheses ="* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table A7: Construction of task contents measures

Task Content Measure ($\boldsymbol{T}$)	Task Items ($\boldsymbol{J}$)
Non-routine cognitive analytical	Analyzing data/information (4.A.2.a.4)[11] Thinking creatively (4.A.2.b.2) Interpreting information for others (4.A.4.a.1)
Non-routine cognitive interpersonal	Establishing and maintaining personal relationships (4.A.4.a.4) Guiding, directing and motivating subordinates (4.A.4.b.4) Coaching/developing others (4.A.4.b.5)
Routine cognitive	The importance of repeating the same tasks (4.C.3.b.7) The importance of being exact or accurate (4.C.3.b.4) Structured vs. unstructured work (4.C.3.b.8)
Routine manual	Pace determined by the speed of equipment (4.C.3.d.3) Controlling machines and processes (4.A.3.a.3) Spending time making repetitive motions (4.C.2.d.1.i)
Non-routine manual physical	Operating vehicles, mechanized devices, or equipment (4.A.3.a.4) Spending time using hands to handle, control or feel objects, tools or controls (4.C.2.d.1.g) Manual dexterity (1.A.2.a.2) Spatial orientation (1.A.1.f.1)

Notes: Based on the elaborations of Hardy, Keister, and Lewandowski (2016b), who build the structure on the work of Acemoglu and Autor (2011).

[11]Codes in brackets corresponds to O*NET Work Activities, Work Context, Abilities and Skills Importance scales. [https://www.onetcenter.org/database.html#all-files]

Table A8: Occupation Coding Changes

	Regular Employee	Self-employed	Employer	Unpaid family worker	Total
Observations	651	2758	3381	13	6803
Percentage	15%	25%	35%	31%	100%

Source: Author's calculations using HLFS.

Table A9: Correlation Table

	PIAAC (Individual-level)			PIAAC (Occupation-level)			O*NET (Occupation-level)		
	Abstract	Routine	Manual	Abstract	Routine	Manual	Abstract	Routine	Manual
PIAAC (Individual-level)									
Abstract	1								
Routine	-0.700	1							
Manual	-0.103	0.098	1						
PIAAC (Occupation-level)									
Abstract	0.535	-0.492	-0.325	1					
Routine	-0.495	0.532	0.294	-0.926	1				
Manual	-0.347	0.313	0.500	-0.649	0.589	1			
O*NET (Occupation-level)									
Abstract	0.394	-0.399	-0.330	0.736	-0.750	-0.660	1		
Routine	-0.356	0.389	0.272	-0.666	0.732	0.544	-0.759	1	
Manual	-0.417	0.405	0.388	-0.778	0.762	0.774	-0.796	0.789	1

Source: Author's calculations using HLFS.

Table A10: Allocation Between Occupations And Tasks

ISCO	Occupations	Emp.Share 2004	Task	Change Emp in	Sh	2004-2012
	Technical and Professional			all	manuf	serv
21	Physical, mathematical and eng prof.	1.1	NR Cog.	0.5	0.5	0.5
23	Teaching professionals	3.9	NR Cog.	-0.5	0.0	-1.3
24	Other professionals	2.3	NR Cog.	0.4	-0.1	0.5
31	Physical, mathematical and eng. assoc.	2.7	NR Cog.	0.2	0.9	0.0
34	Teaching associate professionals	3.6	NR Cog.	0.7	0.2	0.9
	Managerial and Health Proff.					
11	Legislators and senior officials	0.6	NR Cog.	-0.4	0.0	-0.8
12	Corporate managers	2.2	NR Pers.	0.9	1.0	0.8
22	Life science and health prof.	0.9	NR Cog.	0.6	0.1	0.8
32	Life science and health assoc. prof.	1.6	NR Pers.	-0.3	0.0	-0.6
41	**Office Clerks**	7.0	R. Cog	-0.3	0.3	-0.9
51	**Personal and Protective Services**	11.3	NRM Pers.	-0.2	-1.0	-0.8
	Sales ticket clerks and other services					
42	Customer services clerks	2.4	R. Cog.	0.4	0.0	0.4
52	Models and salespersons	6.3	NRM Pers	1.4	0.3	1.6
91	Sales and services elementary occs.	7.9	NRM Phys.	0.4	0.1	0.2
	Routine Operators					
73	Precision, handicraft and related	1.1	R. Man.	-0.2	-0.2	0.1
74	Other craft and related trade work.	7.8	R. Man.	-2.4	-5.1	-0.1
81	Stationary-plant and related operators	1.3	R. Man.	-0.3	-0.2	-0.1
82	Machine operators and assemblers	7.6	R. Man.	-1.0	0.1	-0.1
	Operators					
71	Extraction and building trades	6.4	NRM Phys.	-0.7	-0.6	-0.2
72	Metal, machinery and related	6.3	NRM Phys.	-0.5	0.1	-0.5
83	Drivers and mobile-plant operators	7.7	NRM Phys.	0.3	0.3	-0.1
92	Agricultural, fishery laborers	3.2	NRM Phys.	0.8	0.0	-0.1

Source: Author's calculations based on the O*NET data and two waves of HLFS data (2004, 2012).

Table A11: ISCO88 and ISCO08 Transition Matrix

Distribution of employed by occupation groups (%), 2012 (ISCO 88 and ISCO 08 transition matrix)
(%, 15 years old and over)

		Occupation (ISCO 08) (%)								
Occupation (ISCO 88) (%)	Total	Managers	Professionals	Technicians and associate professionals	Clerical support workers	Service and sales workers	Skilled agricultural, forestry and fishery workers	Craft and related trades workers	Plant and machine operators and assemblers	Elemantary occupations
Total	24.821	1.504	2.173	1.338	1.490	4.104	4.906	3.372	2.391	3.543
Legislators, senior, officials and managers	1.911	1.489	17	1	0	403	1	0	0	0
Professionals	1.931	0	1.928	3	0	0	0	0	0	0
Technicians and associate professionals	1.575	9	228	1.215	4	20	0	99	0	0
Clerks	1.736	0	0	56	1.485	194	0	0	0	0
Service workers and shop and market sales workers	3.181	7	0	7	0	3.144	0	0	0	24
Skilled agricultural, and fishery workers	4.868	0	0	0	0	6	4.859	0	0	2
Craft and related trades workers	3.208	0	0	18	0	0	0	3.119	44	27
Plant and machine operators and assemblers	2.539	0	0	38	0	0	0	154	2.347	0
Elemantary occupations	3.872	0	0	0	0	336	46	1	0	3.490

TurkStat, Household Labour Force Survey, 2012

Figures in table may not add up to totals due to rounding

Source: 2012 HLFS data package from TurkStat.