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WAGE INEQUALITY AND LABOUR MARKET POLARIZATION IN TURKEY? *

Zühal ÖZBAY DAŞ[1]

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Abstract

This study investigates the evolution of wage inequality and "polarization" in Turkey's labour market from 2004–2017. After application of a stacked first difference ordinary least squares (OLS) estimation, the dynamic system method of moments estimation technique (SYS-GMM) was applied to show the association between use of technology and its interaction with the occupation wage categories and wage growth. The results show that there is no clear indication of wage polarization in Turkey. The study also proposes an alternative way by using annual supply of industrial robots to show the interaction between adoption of technology and occupation wage growth in Turkey.

Key words: *Wage inequality, Occupations, Polarization, Technical change*

JEL codes: *J21, J24, J31, Obt33*

TÜRKİYE'DE ÜCRET EŞİTSİZLİĞİ VE İŞGÜCÜ PİYASASI KUTUPLAŞMASI*

Öz

Bu çalışma, 2004-2017 yılları arasında Türkiye işgücü piyasasında ücret eşitsizliğinin ve "kutuplaşmanın (polarizasyonun)" gelişimini incelemektedir. Önce OLS (Stacked First Difference) metodu kullanılmış, sonrasında ise teknoloji kullanımı ile mesleklerin ücret kategorileri ve artışı arasındaki etkileşimi anlamak için SYS-GMM tekniği uygulanmıştır. Sonuçlar, Türkiye'de ücret kutuplaşmasına yönelik net bir bulguya rastlanılmadığını göstermektedir. Çalışma ayrıca, Türkiye'de teknolojinin uyarlanması ile meslek gruplarına göre ücret artışı arasındaki etkileşimi göstermek için yıllık endüstriyel robot tedarikini kullanarak alternatif bir yol önermektedir.

Anahtar kelimeler: Ücret eşitsizliği, Meslekler, Kutuplaşma, Teknik değişim

JEL kodları: J21, J24, J31, O33

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[1] Fenerbahce University, Department of Economics Atatürk Mah. Ataşehir Bulvarı, Metropol İstanbul, 34758, Ataşehir- İstanbul Phone: +90 216 910 1907 E-mail: zuhal.ozbay@fbu.edu.tr, 0000-0002-8135-047X

1. Introduction

There is a substantial body of research that seeks to reveal the underlying factors that stimulate wage inequality between skilled and unskilled workers. Technology is considered as one of the factors that increases the relative demand for skilled labour: in short, technology is supposed to be skill-biased (Katz and Murphy, 1992; Autor *et al.* 1998; Acemoglu and Autor, 2011). However, a significant number of studies have recently shown that skill premiums did not monotonically increase during the late twentieth century and beginning of the twenty-first century (Autor *et al.* 2003; Spitz-Oener, 2006; Autor and Dorn, 2013). According to some studies (Goos *et al.* 2014; Harrigan *et al.* 2016; Adermon and Gustavsson, 2015), particularly in developed economies, technology differentiates the employment and wage growth of different skill levels and triggers an increase in employment and wage growth in both high- and low-skilled labour, while medium-skilled workers lose a substantial share of income and employment. Researchers call this phenomenon "job polarization" and/or "wage polarization" (Goos and Manning, 2007; Autor *et al.* 2006).

Since 2004, overall wage inequality (90/10 log wage differential) has decreased in Turkey, while the employment and income shares of lower-skilled groups (particularly elementary occupations) have increased. Lower tail wage distribution (50/10 log wage differential) diminished after the 2000s (Ozbay Das, 2017). In fact, an increase in the income and employment shares of high-skilled groups (professionals and managers) from 2004–2017 shows fluctuating patterns. On the other hand, I might say that the adoption of technology has increased consistently, since, according to the International Federation of Robotics, the estimated annual supply of industrial robots has increased by more than five times from 2007–2017 (World Robotics, 2018). As Meschi et al (2016) pointed out, Turkey, a high-middle-income country, has certain characteristics, such as strong trade relationships with developed economies, particularly the EU, so technological upgrading is possible through imports, while the country itself has the indigenous domestic capacity to innovate and "absorb new technologies" (Meschi et al. 2016). Thus, how these recent technological changes, particularly in IT development, affect the employment and wage growth of different skills and tasks requires extensive research in the case of a country, which is adopting technology, but also producing technology to some extent.

In this context, this study aims to investigate the evolution of wage inequality and "polarization" in the labour market in Turkey from 2004–2017. The next section explores the literature, while the third section introduces the data used in the analysis. The fourth section is devoted to wage and employment trends in Turkey. Empirical analysis and the results are discussed in the fifth section. The final section concludes.

2. Literature Review

The polarization literature starts with a study by Autor *et al.* (2003), who establish occupational skill requirements as measurement units. They form a model that linked skills and tasks, and categorize each task as either non-routine manual, routine manual, non-routine interactive, routine cognitive, and non-routine analytical[2]. In their analysis, routine tasks refer to tasks that can be "accomplished by machines following explicit programmed rules" (Autor *et al.* 2003, p. 1283), while non-routine tasks are "tasks for which the rules are not sufficiently well understood to be specified in computer code and executed by machines" (p. 1283). They showed that computers can substitute for routine tasks but are complementary to non-routine tasks, and the decline in the price of computers leads to a decrease in the demand for employment for routine tasks. Spitz-Oener (2006) also found similar observations in Germany using four cross-sections of 1979, 1985/1986, 1991/1992, and 1998/1999.

Goos *et al.* (2014) describe the phenomenon articulated by Autor *et al.* (2003) as routine-biased technical change (RBTC) (or task-biased technical change, which is used interchangeably), and state that "recent technological change is biased towards replacing labour in routine tasks" (p. 2509). This approach is well suited to explain the patterns in labour markets since the 1990s in some industrialized countries (Autor *et al.* 2008; Dustman *et al.* 2009). Autor *et al.* (2006) and Goos and Manning (2007) refer to this phenomenon as *polarization*. Polarization is defined as "the simultaneous growth of the share of employment in high skill, high wage occupations and low skill, low wage occupations" (Acemoglu and Autor, 2011, p. 1070). In this framework, Autor and Dorn (2013) analysed low-skilled service jobs that grew by 30 percent in the United States in terms of working hours from 1980–2005. This trend contrasts with the trend of other low-skilled jobs, such as operative and assembler occupations. They hypothesized technological improvements that substitute routine jobs[3] lead to low-skilled workers switching to service jobs. These service jobs require personal communication or geographical proximity and thus are not directly affected by technological changes (Autor and Dorn, 2013, p. 1590). Acemoglu and Autor (2011) formed a Ricardian model of the labour market that allows for the distinction between skills

[2] Examples of each task categories are as follows: non-routine manual: truck driving; routine manual: repetitive assembly; non-routine interactive: persuading, selling; routine cognitive: record keeping, calculation; non-routine analytical: forming/testing hypothesis (Autor et al., 2003, p.1286)

[3] In their analysis, they formed a RTI (Routine Task Intensity Index) for all occupation categories and reduced the broader occupation categories into three as abstract, routine and manual (Autor and Dorn, 2013, p.1593).

and tasks, thus permitting the impact of machines and offshoring to be seen. The distinction between skills and tasks is important because a worker of “a given skill can perform a variety of tasks” (Acemoglu and Autor, 2011, p.1045).

Polarization in labour markets is not only pervasive in the United States but in most industrialized economies. Goos *et al.* (2014) show that this assumption holds for 16 Western economies. In addition, Harrigan *et al.* (2016) found some evidence of labour market polarization in France from 1994–2007 and underlined that firms with more “techies”, that is, technology-related occupations, experienced faster and greater polarization from 2002–2007. Adermon and Gustavsson (2015) showed that job polarization was also prevalent in Sweden from 1975–2005, yet claimed that “task-biased technological change” has the explanatory power for change in within-occupation wage differentials but not between occupations. Coelli and Borland (2016) reported job polarization for Australia in the 1980s and 1990s. Dauth (2014) measured job polarization for 204 local labour markets in Western Germany and found that urban areas show exclusive characteristics where job polarization mainly occurs.

On the other hand, Antonczyk *et al.* (2010) compare trends in wage inequality between the United States and Germany by separating age, time, and cohort effects. They found some evidence of “technology-driven polarization of labour markets” but stated that the wage inequality patterns in the two countries differed dramatically, as not only technology but also differences in institutional factors might have played significant roles in wage distribution in these two countries. Similarly, Firpo *et al.* (2011) compute the contribution of different factors, such as technological change, offshoring, and de-unionization, to wage inequality in the United States using a decomposition method. Their results suggest that de-unionization and technological change played a significant role in the 1980s and 1990s; afterwards, offshoring gained in importance.

The literature related to labour market polarization in developing countries is limited and has only gained momentum in recent years. Xu (2017) found evidence of labour market polarization due to export shocks in China (Xu, 2017, p. 32). Rejinders and de Vries (2018) documented “an increase in the share of non-routine jobs in total employment for a group of emerging and advanced countries during the period of 1999–2007”[4] (2018, p.3). They further pointed out that the countries like China, Poland and Turkey which are offshore destination countries experienced a decline in the relative number of non-routine jobs

[4] 27 European member countries, Australia, Brazil, China, India, Indonesia, Japan, Mexico, Russia, South Korea, Taiwan, Turkey and the United States

because of task relocation. However, for these countries, "technological change was the dominant force behind employment changes" (2018, p.4) Medina and Posso (2010) analysed the effects of skill-biased technological change (SBTC) and task-biased technological change (TBTC) on labour markets in Colombia, Brazil, and Mexico, and showed that labour polarization due to TBTC was evident for Mexico and Colombia but not for Brazil. Sarkar (2017) tested job polarization in India and documented a decrease in the employment share of medium-skilled routine-intensive occupations due to mechanization and technological upgrading within Indian industries. Sarkar (2017) argued, however, that the "increase in employment in both low-skill and high-skill occupations is more of a result of growing self-employment in the informal sector in urban India" (Sarkar, 2017, p. 1).

Akçomak and Gürcihan (2013) first analysed job polarization in Turkey using TURKSTAT's Household Labour Force Survey (2004–2010). They used Firpo *et al.*'s (2011) method to show that occupation matters more than sectoral analysis when explaining wage polarization in Turkey. Akçomak (2014) also discussed the role of outsourcing and offshoring and recommended further study of their effects on the labour market in Turkey.

Popli and Yılmaz (2016) investigated wage inequality trends in Turkey using detailed decomposition analysis and also analysed the occupational task measures and their effects on wage inequality from 2002–2010. They applied Firpo *et al.*'s (2009) decomposition technique and showed that "changes in the returns to routine tasks explain the fall in inequality in the upper tail of the wage distribution for both men and women", which is contrary to the expectations of the polarization argument (Popli and Yılmaz, 2016, p. 92). On the other hand, Acar-Erdogan and Del Carpio (2019, p.49) reported an increase in "using the cognitive skills with better quality jobs instead of the manual skills associated with lower quality jobs" in Turkish labour market. Moreover, they documented that while "non routine manual physical and routine physical skills are becoming less dominant", non-routine and routine cognitive skills are becoming more dominant, particularly the highest increase in the use of routine cognitive skills has been observed among bookkeepers or call center operators. They also reported that an increase in employment in all three types of occupations, low skill, middle skill, high skill, between 2009 and 2017 is observed, even in 2012 and 2012, "high skill occupations decreased", but after 2014, they increased (p.48). Therefore, their results show the differences in terms of employment in three types of occupations between subperiods. Eriş-Dereli (2021) also underlines the role of occupations in overall wage inequality in Turkey by showing that even though within occupation wage inequality is the main driver of the overall wage inequality for the period of 2005-2017, the between occupation wage inequality plays an increasingly important role in the overall wage inequality.

3. The Data

Household Labour Force Surveys (HLFS) from Turkish Statistical Institute (TURKSTAT) are used in this analysis. The surveys present the detailed information about gender, age, occupation, working hours, earnings, economic activities etc. Basically, due to difference in occupation information in the surveys, between 2004-2012, and 2012-2017, the two periods are analysed separately. The sample consists of workers (regular or causal employees) who are between 15 and 64 years old. Following Bakış and Polat (2015), workers working less than 8 and more than 84 hours are not included into the analyses in order to eliminate the possible biases. Besides, 1% of up and bottom (outliers) wage values are trimmed in the analysis.[5]

Hourly wage is used in the analysis by dividing monthly wage data to total hours worked in a month. Total hours worked in a month is calculated by transforming weekly hours into monthly hours by multiplying the number of hours per week usually worked in main job by 4.33.[6] The wage from main activity is assumed to be basis of monthly wage. That is, only the regular payments are of the scope (Bakış and Polat, 2015). Nominal hourly wage is deflated by Consumer Price Index (CPI).

For occupation, between 2004 and 2012, the data comprise 2 digit ISCO88, while between 2012 and 2017, the data are categorized into 2 digit ISCO08. The International Standard Classification of Education (ISCED, 1997) is taken as a basis for the level of educational attainment in the survey.

To test the recent technological changes on wage distribution, first Routine Task Intensity Index (RTI) is used in this study. Goos et al. (2014) calculated RTI indices for ISCO88. They construct RTI indices based on Autor and Dorn (2013) study as "the difference between the log of Routine tasks and the sum of the log of Abstract and the log of Manual tasks[7], which (they) normalize to have mean zero and unit standard deviation across our occupations" (Goos et al, 2014, p.4 (Appendix)). RI_k, MI_k AI_k denotes the routine, manual, and abstract measures respectively in each occupation *k* (Autor and Dorn, 2013, p.1570). Following Goos et al (2014), teaching professionals and teaching associate professionals

[5] For more detail about data, see (Ozbay Das, 2017)

[6] Tansel and Bodur 2012), Bakış and Polat (2015) followed the same procedure (the former divided, the latter multiplied with 4.3).

[7] $RTI_k = Ln\ (RI_k) - Ln\ (MI_k) - Ln(AI_k)$.

(ISCO 23 and 33); skilled agricultural and fishery workers (ISCO 61); subsistence agricultural and fishery workers (62) and agricultural, fishery and related labourers (ISCO 92) are dropped from the analysis. In order to be compatible with ISCO08, legislators and senior officials (ISCO 11) are not dropped from the analysis.

The categorization of all occupations in ISCO88 as abstract routine and manual is formed according to RTI Index and the explanations made by International Labour Organization ILO (International Organization, n.d). For ISCO08, there are no RTI indices available in the literature. For broad categorization of ISCO08, OECD (2017) report is used. Teaching professionals (ISCO 23), market-oriented skilled agricultural workers (ISCO 61), market-oriented skilled forestry, fishery and hunting workers (ISCO 62), subsistence farmers, fishers, hunters and gatherers (ISCO63) and agricultural, forestry and fishery labourers (ISCO92) are dropped from the analysis. (For broad occupation categories as abstract, routine and manual for ISCO88 and ISCO08 occupation categories, see Appendix table A1 and table A2).

In addition to RTI, estimated annual supply of robots statistics is also included into the model to see the interaction between different types of occupations and robot usage in the whole country. The data is taken from World Robotics Report by International Federation of Robotics for the period 2005-2017 (World Robotics Report, 2018 and 2007).[8]

4. The Wage And Employment Trends In Turkey

Turkey's labour market has undergone major changes in the last 40 years. The economic paradigm has changed dramatically. Parallel to this change in the economic environment, the education system in Turkey also experienced significant changes during the past two decades. Educational attainment progressed at all levels; the number of university graduates in the labour market has also increased dramatically (Council of Higher Education)[9] and the unions have lost power (OECD)[10]. All these factors have affected the wage distribution in Turkey.

[8] For the year 2004, to see the supply of robotics for Turkey, please see (Koca, Dogan and Taplamacıoğlu, 2009)

[9] The number of universities has increased from 50 in 1992 to 183 in 2016. (Council of Higher Education, https://istatistik.yok.gov.tr. Accessed: 31.05.2017)

[10] In Turkey, Organization For Economic Cooperation and Development (OECD) statistics reflect that trade union density has declined from 32.9 in 1994 to 25.1 in 2002 and further decreased to 7.8 in 2011 (OECD.Stat. Accessed: 03.08.2017)

Figure 1 Overall* and Residual** Log Real Hourly Wage Ratios, 2004-2017

Source: Author computations from 2004-2017 HLFS datasets.

* It represents 90/10 log wage differential which is calculated as log wage difference between 90th and 10 percentiles.

** It represents 90/10 log wage differentials of residuals which are computed from the regression of Mincerian equation. For calculating the years of schooling, 0, 2, 5, 8, 11, 15, and 17 values are assigned for illiterates, read and write only, primary school, middle school and basic education, high school, university, and post university graduates respectively. (Tansel and Bodur, 2012, p.121), (Ozbay Das, 2017).

Wage inequality in Turkey has exhibited a decreasing trend since the 1990s but remains high compared to many developed countries. Moreover, there is an increasing trend in the employment and income shares of the lowest-skilled groups. Figure 1 represents the overall and residual wage inequality for the past 14 years. The overall wage inequality (90/10 log wage differential) first decreases and then rebounds slightly up to 2013, declining in 2016. The lower tail (50/10) wage inequality decreases throughout almost the entire period while the upper tail wage inequality (90/50) fluctuates, particularly after the global crisis, when it reaches its maximum level. Ozbay-Das and Dogruel (2017) showed that wage inequality among university graduates increased for 90–50 spreads for the successive decades of the 1990s to 2000s. Residual inequality measures showed that up to 2012, the 90/10 log wage differential followed a decreasing trend, rebounding slightly between 2008 and 2012, but did not rise higher than the previous level. Then, a substantial decrease was observed after 2012. The upper tail distribution of residuals was stable up to 2012 and then showed a decreasing pattern. The 50/10 wage inequality measure also decreased until 2008, remained stable between 2008 and 2013, and then decreased thereafter. Indeed Kent and Sefil-Tansever (2021) also documented a decrease in wage the inequality at the upper tail of distribution in Turkey for the years between 2006 and 2014, while they observed an increase in the wage inequality at the lower tail distribution. [11]

Relatively faster real wage growth for the lower percentiles from 2002–2007 could have been caused by a dramatic increase in the minimum wage (24.3%), while in the private sector, net wages increased by only 3.5% in 2004. An increase in the minimum wage is therefore highly likely to affect the lower tail wage distribution.

On the other hand, from 2011–2015, the increase in the minimum wage does not fully explain the relatively greater increase in the real wage of lower tails because in 2013 and 2014, minimum wage increases accounted for only 1.8% and 1.2% [1]respectively. Therefore, there must have been other factors that played significant roles in explaining this increase. Technological change is another significant factor that might affect lower and, to some extent, upper tail real wage growth. Figure 2 provides a clue towards polarization from its rough U-shaped appearance. From 2004 to 2017, the real wage in the medium tail increases relatively less than the real wage in the lower and upper tails.

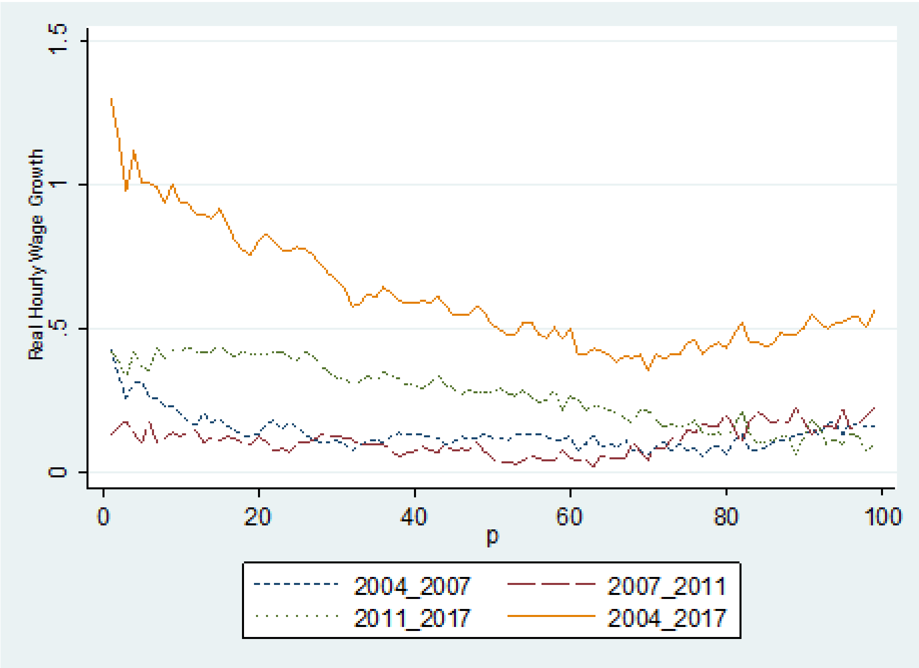
Figure 3 shows the log change of real hourly wages and labour shares (in efficiency units) by education level and gender. Following Bakış and Polat (2015), all series are normalised to zero in 2004; the graphs show the cumulative change since then. Real hourly wages increase for both male and female employees in all education categories until 2013; after 2013, a slight decrease is observed for both males and females with college degrees. In 2016, the real wage for below college degree categories jumps, most likely due to the large

[11] Kent and Sefil-Tansever (2021) employed different data set, Structure of Earnings Survey, from TURKSTAT in their analysis.

[12] In 2016, there was, however, another 23.5 percent increase in the minimum wage in real terms, which will affect the lower tail wage distribution and could be partly seen in Figure 1

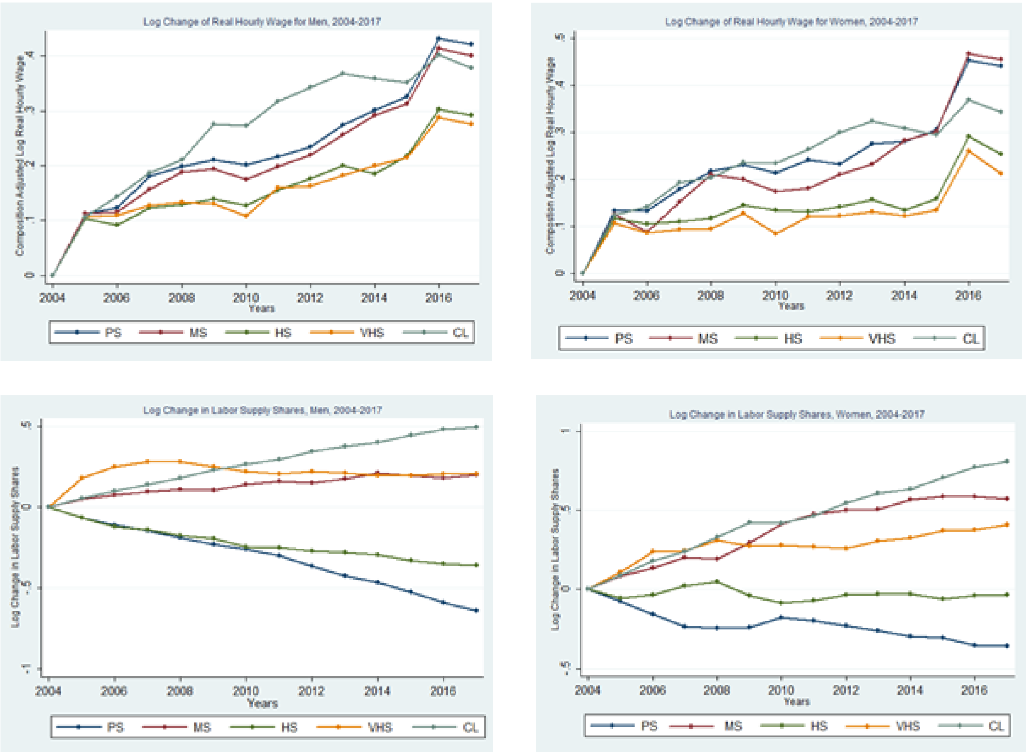
increase in minimum wage. The real wage growth of middle school graduates is mostly lower than the real wage growth of primary school graduates. The share of primary school and high school graduates declines for both male and female categories, but among the high school graduates, this decline is most observed among male high school graduates. The share of vocational high school graduates first increases and then decreases or remains stable since 2009.

Figure 2 Percentile Real Hourly Wage Growth, 2004-2017



Source: Author computations from 2004-2017 HLFS dataset

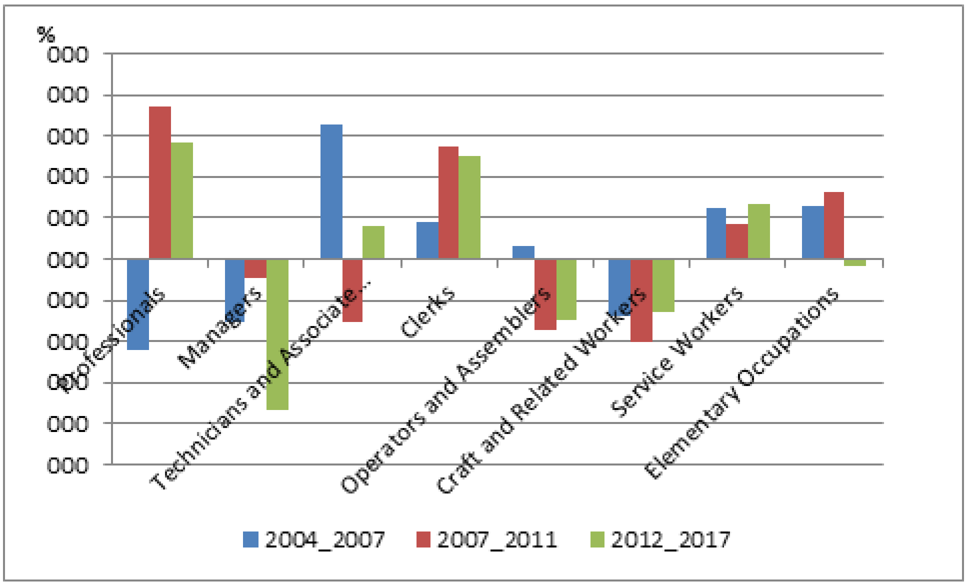
Figure 3 Log Change of Real Hourly Wages and Labour Shares (in Efficiency Units) For Men and Women, 2004-2017



Source: Author's calculations from HLFS. PS, MS, HS, VHS, CL stands for Primary School or Low, Middle School, High School, Vocational High School and College respectively.

In order to understand whether job polarization occurred during 2004–2017 in Turkey, it is beneficial to check the pattern of employment changes in certain occupation groups during this period. When occupations are ordered according to their mean payments from highest to lowest, the changes in the employment shares of these groups are depicted (see Figure 4). The left-side figure shows the professionals that have the highest mean real hourly wage, while the right-side shows the elementary occupations that are given the lowest wage in 2004. If Turkey's labour market follows the same pattern as the labour markets in developed economies, the employment shares of both the highest and lowest paid occupations (particularly, service and elementary) should increase, as the polarization literature suggests (Autor *et al.* 2003; Spitz-Oener, 2006). The figure does not, however, clearly show this phenomenon. First, the highest paying occupations—for example, professionals, managers, technicians, and associated professionals—do not continuously increase because while the employment share of professionals decreases from 2004–2007, it increases from 2007–2011 and 2012–2017. The employment share of managers decreases for all periods. The employment share of technicians and associated professionals decreases only from 2007–2011. On the other hand, the employment share of clerks increases for all three periods, which is contrary to what was expected; in Europe, for instance, it decreased from 1993–2010 (Goos *et al.* 2014, p. 2512). What is compatible with the developed countries' experiences, however, is that an increase in the employment shares of both service workers and elementary occupations is observed for all periods, and there is a decrease in the employment shares of operators, assemblers, craftsmen, and related workers' occupation categories throughout the period.

Figure 4 Percentage Change in Employment Shares by Occupation, 2004-2011, 2012-2017



Source: Author's calculations from HLFS 2004, 2007, 2011, 2012, 2017. Demographic groups consist of 5 education category, 10 age group, two gender groups and 8 occupation groups. For computing employment shares of broad demographic categories, fixed weight approach is used for the two different periods as 2004-2011 and 2012-2017 (Ozbay Das, 2017).

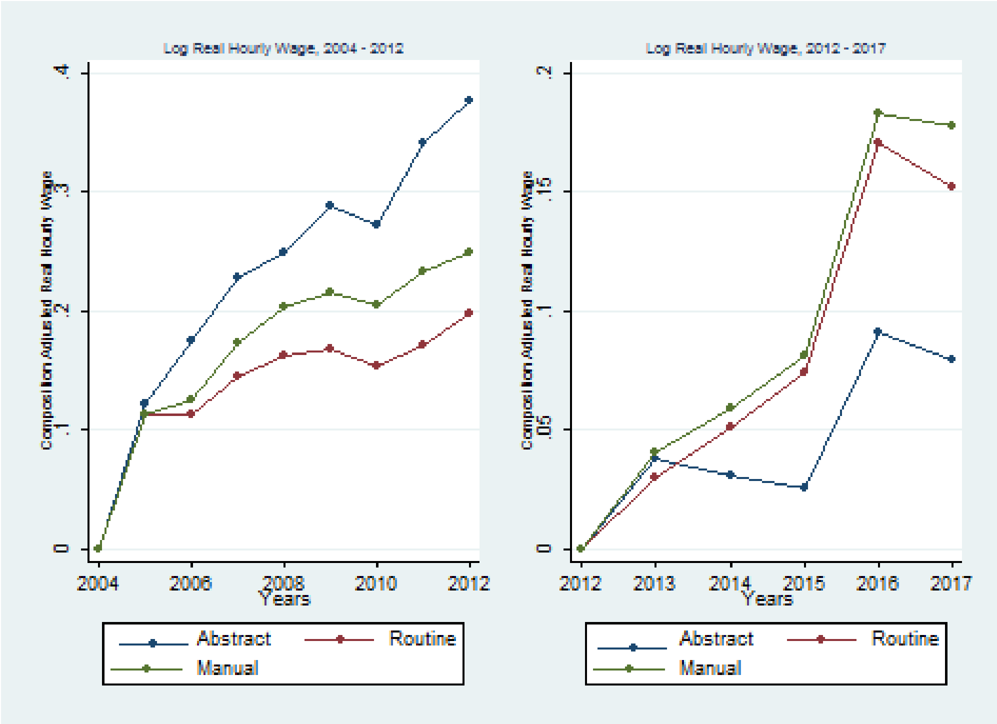
Table 1 shows the log change in real wages and employment shares of broad occupation categories for both men and women. The highest change in real wages is seen in the professional occupation category for males, while the manager category experiences the highest increase in the real wage for females from 2004–2007. An increase in the real wage of professionals decelerates over the subsequent periods and decreases to 5.6 for males and 2.9 for females from 2012–2017. The employment share of professionals first severely decreases from 2004–2007 and then rebounds from 2007–2011. It shows a moderate increase for males and a steady increase for women. Employment in the manager category declines for all periods among men but increases among women up to 2011, then decreases. The employment share of operators and assemblers decreases in the last two periods. On the other hand, the employment shares of service workers and elementary occupations show a distinct pattern among female workers, since employment increases dramatically throughout the period. As in the case of the United States (Autor and Dorn, 2013, p. 1556), the increase in the employment shares of elementary occupations and service workers exceeds that of other low-skilled occupations in Turkey. This could be from the reallocation of low-skilled labour used to perform routine tasks in service occupations (employment polarization) due to a decrease in the price of computer capital (Autor and Dorn, 2013, pp. 1553–1159).

Table 1 Log Real Wage and Employment Shares in 8 Occupation Broad Categories For Male and Female, 2004-2011, 2012-2017

Years	**Change in Log Real Wages**			**Change in log employment shares**		
	2004-2007	**2007-2011**	**2012-2017**	**2004-2007**	**2007-2011**	**2012-2017**
Male						
Professionals	28.61	15.62	5.61	-17.79	17.02	9.22
Managers	23.22	12.94	10.57	-10.05	-3.99	-24.10
Tech&Assoc. Prof	16.15	6.06	10.25	16.53	-12.89	4.16
Clerks	11.95	4.83	5.21	-1.07	8.66	13.33
Operators and Assemblers	14.28	3.46	16.42	1.49	-8.89	-8.16
Craft and Related Workers	19.49	2.14	17.43	-5.44	-11.10	-7.72
Service Workers	18.42	6.03	16.46	3.10	-0.03	-0.37
Elementary Occupations	12.86	5.72	21.17	5.31	4.32	-6.01
Female						
Professionals	26.52	9.19	2.92	7.95	16.69	21.12
Managers	27.89	17.55	13.59	13.63	11.99	2.50
Tech&Assoc. Prof	17.44	2.78	4.29	11.53	4.50	3.13
Clerks	12.18	3.68	7.61	13.61	19.22	9.31
Operators and Assemblers	7.70	6.51	26.49	3.87	-10.79	-2.03

Source: Author's calculations from HLFS 2004, 2007, 2011, 2012, 2017. For computing employment shares and composition adjusted wage of broad demographic categories, fixed weight approach is used for the two different periods as 2004-2011 and 2012-2017 (Ozbay Das, 2017).

Figure 5 Log Real Hourly Wage Change for 3 Broad Categories of Occupation, 2004-2012, and 2012-2017



Source: Author's calculations from HLFS 2004, 2007, 2011, 2012, 2017. For computing composition adjusted wage of broad demographic categories, fixed weight approach is used for the two different periods as 2004-2011 and 2012-2017. All series are normalized to zero in 2004, and then the graphs show the cumulative change (Ozbay Das, 2017).

Figure 5 shows the change in real wages and employment shares of occupations, yet it is difficult to say that employment and wage polarization occurred in Turkey since the increase in real wages and employment shares of abstract occupations relative to the routine ones seems unclear.

5. Model And Empirical Findings

Acemoglu and Autor (2011) studied "the evolution of wages by skill groups" (p. 1153) and stated that the prices of tasks have an effect on the wages of different skill groups. That is, if the market value of specific tasks declines, the wage of the skill group having the comparative advantage of those specific tasks declines. The initial specialization of abstract-intensive, routine-intensive, and manual-intensive occupations constitutes the basis for the skill groups, and is counted as the proxy for comparative advantages in their analysis (Acemoglu and Autor, 2011, p. 1153). According to the above assumptions and the empirical model suggested by Acemoglu and Autor (2011), the following model is formed:

$$\Delta w_{sej\tau} = \sum \beta_t^A . \gamma_{sej}^A . 1[\tau = t] + \sum \beta_t^S . \gamma_{sej}^S . 1[\tau = t] + \delta_\tau + \phi_e + e_{sej\tau} \qquad (1)$$

$w_{sej\tau}$ stands for the mean log wage of a specific group in year t (s reflects gender, e reflects education group, j reflects age group) and $\Delta w_{sej\tau}$ is the change in mean wage of the demographic group during the period τ.

δ, ϕ are the vector of time and education dummies. γ_{sej}^A, γ_{sej}^S, γ_{sej}^R, are the employment shares of the abstract, service and routine occupations in 2004. Due to data constraints, 2004 was selected as the start date in this study (Acemoglu and Autor (2011) start with 1959). $\gamma_{sej}^A + \gamma_{sej}^S + \gamma_{sej}^R = 1$ and γ_{sej}^R is the reference group. "β_t^A and β_t^S coefficients in this model estimate the decade slopes on the initial occupation shares in predicting wages by demographic group" (Acemoglu and Autor, 2011, p.1153). δ_τ shows the comparative advantage of the routine tasks for each period.

The hypothesis of this model is to investigate whether job polarization occurred from 2004–2012 and 2004–2017. The stacked ordinary least squares (OLS) first difference method was employed to estimate Equation 1. The estimation suffered from a shorter time period and the effect of technological improvement on occupation was still ambiguous. Moreover, endogeneity problems might occur due to omitted variables since each time period contains other information regarding the comparative advantage of the three broad occupation categories during the stacked OLS estimation. However, after the 2000s, there were huge improvements, particularly in IT technology. Therefore, the start date of 2004 may provide some tentative findings regarding the occupational changes in Turkey.

The empirical findings in the first column in Table 2, which is an estimate for males, show that only the 2004–2007 trend dummy is significant and positive, but the second column, which includes education dummies in the estimation, indicates that two time dummies are significant and positive for males. Thus, there is an increasing comparative advantage of routine tasks for males from 2004–2007 and 2008–2012 since “time intercepts estimate wage trends for demographic groups that hold comparative advantage in routine tasks” (Acemoglu and Autor, 2011, p. 1154). In line with the time intercepts, there is no evidence of an increase in wages for the abstract and manual occupations among males; if there is, a decrease is observed for these categories. Conversely, columns 3 and 4, which are the estimates for females, show that the abstract and particularly the manual categories from 2007–2012 are significant and positive, which is consistent with expectations. An increase in the relative wages of female demographic subgroups that have initial specializations in manual tasks or, to some extent, abstract tasks, are observed in the estimation. Time intercepts hardly interpret the movements in the wage change of routine categories, but from 2007–2012, the sign is negative, which is in line with the theory.

Table 3 covers the estimations from 2004–2017. The results show that for males, the relative wage of abstract tasks from 2011–2017 and the relative wage of manual tasks from 2008–2011 decreases. Trend dummies are positive for all periods for males. On the other hand, the change in the real wage for manual groups is relatively higher from 2007–2011 among women. It is difficult to see an increase in the relative wage of abstract tasks for women from 2004–2007 and 2008–2011. The trend dummies are also positive in this period. Moreover, a decrease in the relative wage of the abstract category is observed from 2012–17; compatibly, trend dummies are positive for that period. Therefore, for the female subgroups, it is not incorrect to state that manual tasks have gained comparative advantage over routine categories up until 2012, yet the situation for the abstract categories seems unclear. The relative wages of the abstract occupation categories have, however, decreased among males, thus the estimation results give no clear indication of polarization.

Table 2 OLS Stacked First Difference Estimates, 2004, 2007, 2012

	Male		***Female***	
	1	**2**	**1**	**2**
Abstract Occupation Share				
2004 share *2004-2007 time dummy	-.125(.116)	-.203(.124)	.0868(.091)	.114(.144)
2004 share *2008-2012 time dummy	.0389(.119)	-.061(.130)	.221**(.088)	.227(.139)
Manual Occupation Share				
2004 share *2004-2007 time dummy	-.177(.171)	-.418*(.226)	.147(.128)	.0859(.137)
2004 share *2008-2012 time dummy	-.131(.174)	-.395*(.237)	.388***(.123)	.302**(.141)
Time Dummies				
2004-2007	.215**(.100)	.355***(.127)	.0371(.060)	.0716(.066)
2008-2012	.137(.103)	.292**(.135)	-.087(.061)	-.0388(.0717)
Education Dummies				
Middle		-.001(.019)		-.014(.028)
High		-.039(.026)		-.0359 (.033)
Vocational High School		-.073*(.038)		-.055(.051)
University		-.039(.061)		-.041(.082)
R squared	0.696	0.716	0.612	0.622
# of Observations	100	100	99	99

Source: Household Labour Force Surveys 2004-2012. Each column shows a separate OLS regression of stacked changes in mean log real hourly wages by demographic group and year, where demographic groups are defined by gender, education, age group. Occupations are categorized into three separate groups as: abstract, routine and manual. Reference category is the routine group in the models (Acemoglu and Autor, 2011, p.1156). Standard errors are in parentheses (Ozbay Das, 2017).

Table 3 OLS Stacked First Difference Estimates, 2004, 2007, 2011, 2017

	Male		***Female***	
	1	**2**	**1**	**2**
Abstract Occupation Share				
2004 share *2004-2007 time dummy	-.125(.112)	-.207*(.116)	.086(.098)	.*0108(.134)
2004 share *2008-2011 time dummy	-.044(.115)	-.142(.121)	.148(.097)	.074 (.131)
2004 share *2012-2017 time dummy	-.261**(.118)	-.373***(.126)	-.350***(.092)	-.420***(.126)
Manual Occupation Share				
2004 share *2004-2007 time dummy	-.178(.165)	-.266(.201)	.147(.139)	.139(.144)
2004 share *2008-2011 time dummy	-.235(.167)	-.338*(.208)	.319**(.136)	.314**(.148)
2004 share *2012-2017 time dummy	.077(.172)	-.031(.216)	-.144(.125)	-.145(.144)
Time Dummies				
2004-2007	.215**(.097)	.280**(.115)	.037(.065)	.047(.069)
2008-2011	.176*(.099)	.250**(.120)	-.073(.066)	-.066(.074)
2012-2017	.244**(.102)	.326***(.126)	.313***(.063)	.313***(.075)
Education Dummies				
Middle		-.003(.015)		.028(.025)
High		-.024(.021)		-.011(.03)
Vocational High School		-.041(.030)		.007(.044)
University		.029(.046)		.052(.069)
R squared	0.81	0.82	0.70	0.71
# of Observations	150	150	150	150

Source: Household Labour Force Surveys 2004-2017. Each column shows a separate OLS regression of stacked changes in mean log real hourly wages by demographic group and year. Standard errors are in parentheses.

An endogeneity problem leads to biased OLS estimates. To address this problem and determine the relation between different tasks and occupation wage levels, the following dynamic empirical models were formed.

The empirical model for 2004–2012 was formulated in the following equation:

$$LNW_{jt} = \beta_1 LNW_{jt-1} + \beta_2 RTI_j + \beta_3 ROB_t + \beta_4 EDUC_{jt} + \beta_5 AGE_{jt} + \beta_6 AI_t + \beta_7 AI_t * ROB_t + \beta_7 MI_t + \beta_8 MI_t * ROB_t + year2005 + year2007 + year\ 2009 + year\ 2011 + u_{jt} \quad (2)$$

The empirical model for 2012-2017 was formulated in the following equation:

$$LNW_{jt} = \delta_1 LNW_{jt-1} + \delta_2 ROB_t + \delta_3 EDUC_{jt} + \delta_4 AGE_{jt} + \delta_5 AI + \delta_6 MI + \delta_7 AI_t * ROB_t + \delta_8 MI_t * ROB_t + year2014 + year2015 + year\ 2016 + year\ 2017 + \pi_{jt} \quad (3)$$

where j= 1,…, N denotes occupation, t= 1,…, T denotes the period and u and π denote error terms.

For the years 2012 and 2017, routine task intensity (RTI) indices for the ISCO08 occupation categories were not available; therefore, for those years, the RTI variable was dropped from the analysis.

LNW_{jt} denotes log transformation of the mean wage level of occupation j at time t. AI refers to the abstract occupation if occupation $\in$AI, AI=1, otherwise 0; RI refers to the routine employment category, if occupation $\in$RI, RI=1, otherwise 0; MI denotes the manual employment share, if occupation $\in$MI, MI=1, otherwise 0. *RI* was used as a reference category. If polarization occurred from 2004–2017, the wages of the abstract and manual categories are expected to grow relatively higher than the routine occupation categories; therefore, the coefficients of *AI* and *MI* are expected to be positive. *ROB* denotes the annual supply of industrial robots and is used as a proxy for the use of technology, *EDUC* denotes the average education level for each occupation category, and *AGE* denotes the average age. RTI (see Appendix) is also a measure that is 'the best way to capture the impact of recent technological progress' (Goos *et al.* 2014, p. 2511). $AI_t * ROB_t$ and $MI_t * ROB_t$ refer to the intersection of the abstract and manual occupation categories with an annual supply of industrial robots; thus, whether the usage of technology on the abstract and manual occupation categories differs can be understood. The year dummies are 2005, 2007, 2009, and 2011, respectively, in the first model. In the second model, the year dummies are 2014, 2015, 2016, and 2017. The equations are estimated for the entire Turkish male and female categories for the articulated periods.

The panel dataset has a short time dimension (T = 9; 6) and a larger cross-section dimension (N = 22; 35), depending on past experiences, and has weak exogenous variables, such as education and age. As Roodman (2009) pointed out, the ''Arellano–Bond (1991) and Arellano–Bover/Blundell–Bond (Arellano and Bover 1995; Blundell and Bond 1998) dynamic panel estimators are increasingly popular. Both are general estimators designed for situations with “small T, large N” panels … a linear functional relationship … one left-hand-side variable that is dynamic … [and] independent variables that are not strictly exogenous” (Roodman, 2009, p. 86). Therefore, the suggested models are consistent with the above assumptions. Blundell and Bond (1998) showed that a shorter period might lead to a weak instrument problem, and this problem can be aggravated under the presence of the persistence of the time-series. In short, “where the number of time periods is small and in the presence of persistence, the SYS-GMM estimator can produce dramatic efficiency gains over the basic Diff-GMM estimator” (Coady and Dizioli, 2017, p. 7). The OLS and least squares dummy variable (LSDV) estimations of the lagged dependent variable refer to the presence of persistence[13]. Therefore, the SYS-GMM method was preferred in this study. To increase the efficiency of the GMM estimation, a two-step procedure is widely suggested (Hwang and Sun, 2015), and as Roodman (2009) suggested, a two-step standard error using Windmeijer’s (2005) correction “seems modestly superior to cluster-robust one-step estimation” (p. 97). Therefore, a two-step system with GMM using Windmeijer’s (2005) correction method was used in this analysis.

As Berk *et al.* (2018) clearly outline, four key diagnostics show the consistency of the SYS-GMM. The first is that the Arellano Bond tests for AR(2) in the first differences should not be rejected. The results in Table 4 show that no second-order serial autocorrelation AR(2) fails to be rejected. The second is that “the instruments should not be correlated with error terms” (Berk *et al.* 2018, p. 4). Hansen’s p-values in Table 4 show the null hypothesis that the over-identification restrictions are valid is failed to be rejected. The third condition underlines the importance of the validity of additional restrictions, and the difference in the Hansen results in Table 4 report that the null hypothesis of the joint validity of the instrument’s subsets cannot be rejected. The final condition is that the number of instruments should be less than or equal to the number of groups (Berk *et al.* 2018) (Roodman, 2009). The final condition is also satisfied, as shown in Table 4.

The estimation results of Equations 2 and 3, which are shown in Table 4, reveal that the log wages of the occupations are strongly associated with their past values for both periods. The association between RTI and wage seems negative, particularly for men in 2004 and

[13] OLS and LSDV estimations showed that that coefficient of lagged dependent variable is as follows respectively: Model 1 OLS: 0.83, LSDV: 0.55; Model 2: OLS: 0.77, LSDV: 0.51; Model 3: OLS: 0.39, LSDV: -0.094; Model 4: OLS: 0.98, LSDV: 0.24; Model 5: OLS: 0.93, LSDV: 0.17; Model 6: OLS: 0.69, LSDV: 0.07

2011, which is suggested in the literature. The supply of robots is strongly associated with the mean wage of occupations in 2004 and 2012, but no clear association is observed for 2012 and 2017. The sign of the abstract occupation dummy is positive but insignificant for both periods for the whole of Turkey, yet in the first period among males, the sign is negative and significant at the 10 percent level. Furthermore, for the second period among females, the interaction terms of the abstract and robot supply are negative. In contrast to the polarization argument, for the manual occupation categories, the sign of manual occupation dummy is negative and significant at the 10 percent level from 2004–2012. This indicates that wage growth for the manual occupation categories and abstract occupation categories among males is less than that of the routine occupation categories; however, this result is not clear from 2012–2017. On the other hand, the sign of interaction between the supply of robots and manual dummies is positive for the first period and significant at the 10 percent level. Therefore, this result shows that the use of robots in this particular category differs in terms of wage growth. On one hand, the results imply the role of technology in wage growth; on the other hand, there is no clear indication of polarization in the Turkish labour market from the results.

Table 4 Wage and Occupation Categories, SYS GMM, 2004-2012, 2012-2017

	Dependent Variable: Log mean Wage of Occupation Category (ISCO88, for 2004-2012, ISCO08 for 2012-2017)					
	2004-2012			**2012-2017**		
	System GMM	System GMM(Male)	System GMM(Female)	System GMM	System GMM(Male)	System GMM(Female)
LNW (-1)	0.711***	0.684***	-0.332**	0.807***	0.698***	0.363*
	(0.0615)	(0.163)	(0.140)	(0.129)	(0.103)	(0.199)
ROB	2.97e-05**	1.94e-05	0.000127*	-2.08e-05	-0.000136	-0.000550
	(1.43e-05)	(2.39e-05)	(6.63e-05)	(8.09e-05)	(8.43e-05)	(0.000619)
RTI	-0.0212*	-0.0405**	-0.132*			
	(0.0118)	(0.0164)	(0.0688)			
EDUC	0.0731***	0.117**	0.450***	0.0408	0.0946***	0.256**
	(0.0163)	(0.0500)	(0.0971)	(0.0411)	(0.0330)	(0.107)
AGE	0.0423***	0.0351*	0.111***	0.0405*	0.0664***	0.153
	(0.00986)	(0.0202)	(0.0277)	(0.0229)	(0.0148)	(0.105)
AI	0.00867	-0.0862*	-0.0951	0.0616	0.0573	0.0394
	(0.0439)	(0.0467)	(0.156)	(0.0448)	(0.0506)	(0.142)
AI*ROB	1.95e-05	2.64e-05	-5.70e-06	-1.41e-05	-2.64e-05	-4.63e-05*
	(1.47e-05)	(2.25e-05)	(6.90e-05)	(1.69e-05)	(2.02e-05)	(2.76e-05)
MI	-0.0486*	-0.0719*	-0.0927	-0.0201	-0.0174	-0.00678
	(0.0278)	(0.0404)	(0.188)	(0.0313)	(0.0356)	(0.0744)
MI*ROB	1.17e-05	2.64e-05*	-5.08e-05	7.31e-07	-1.78e-06	-1.48e-05
	(1.03e-05)	(1.59e-05)	(6.32e-05)	(1.32e-05)	(1.23e-05)	(2.44e-05)
Instruments	19	19	21	35	35	23
Groups	21	21	21	35	35	35
Hansen p value	3.56	6.24	11.78	26.63	27	16.80
Difference in Hansen	0.69	4.43	0.26	20.95	16.95	4..77
AR (2)	0.64	0.69	-1.68*	1.45	1.43	0.14
Observations	168	168	168	175	175	175

Notes: SYS GMM is used for all models. In model 1, 2 and 3, collapse command is used in Stata. Instrument variables are RTI, annual supply of robots, AI, MI dummies and its interaction terms with supply of robots, time year dummies and all available lags used for education and age. Robust (Windmeijer) standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

* Hansen p value is 0.093 in the third estimation, therefore the null hypothesis could not be rejected at 5 percent significance, but be rejected at 10 percent significance.

6. Conclusion

Wage distribution in Turkey could be affected by many factors such as an increase in the supply of educated labour and changes in labour market institutions, including the dramatic increase in the minimum wage in 2004 and de-unionization since the 1990s. Moreover, as the literature frequently points out, recent developments in technology are highly likely to affect the labour market. In this context, this study revealed that polarization in Turkish labour market is not evident, but there are still some indications of at least two structural changes. The first is an increase in the relative wages of female demographic subgroups that have initial specializations in manual tasks. The second is that the contribution of robots to wages is not robust in the abstract occupation categories for the whole of Turkey, but is negative among females in 2012 and 2017. However, the contribution of robots to wages was positive in the manual occupation categories from 2004–2012, while the wage growth of the manual and abstract occupation categories among men was less than that of the routine occupation categories, which is contrary to the polarization literature of that particular period. On the other hand, the association between the routine task intensity index and wage growth is negative, which is consistent with the polarization phenomenon. Therefore, the relationship between technology and wages is rather complex in the Turkish labour market, and the developments in the service sector over the past few decades and the association between technology and the abstract occupation categories requires further study.

Furthermore, a deeper understanding of each occupation category is needed to clarify the shifts in occupations. In this respect, detailed information about tasks relating to occupations will make the analysis more robust by enhancing the understanding of technology on wage distribution in Turkey, since it would be possible to eliminate factors other than technology that affect the wage structure. Unfortunately, occupation data are available only for two-digit ISCO88 and ISCO08 levels, and there is no available data that reflect the task composition of each job that workers usually perform. Studies focusing on the relation between tasks and occupations in Turkey would enrich the understanding of the impact of technology on labour markets in emerging economies

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Appendix

Table A1 Occupation Categories (ISCO88) and RTI

Occupation	ISCO88 Code	Category	RTI Index
Legislators	11	Abstract	
Corporate managers	12	Abstract	-0.7469759
Managers of small enterprises	13	Abstract	-1.522734
Physical, mathematical and engineering professionals	21	Abstract	-0.8220372
Life science and health professionals	22	Abstract	-1.000168
Other professionals	24	Abstract	-0.732465
Physical and engineering associate professionals	31	Abstract	-0.3973301
Life science and health associate professionals	32	Abstract	-0.3327664
Other associate professionals	34	Abstract	-0.4424283
Office Clerks	41	Routine	2.240688
Customer service clerks	42	Routine	1.406782
Personal and protective service workers	51	Manual	-0.5976907
Models, salespersons and demonstrators	52	Manual	0.0534066
Extraction and building trades workers	71	Manual	-0.1854081
Metal, machinery and related trade work	72	Routine	0.4568464
Precision, handicraft, craft printing and related trade workers	73	Routine	1.588948
Other craft and related trade workers	74	Routine	1.237669
Stationary plant and related operators	81	Routine	0.3230704
Machine operators and assemblers	82	Routine	0.4925116
Drivers and mobile plant operators	83	Manual	-1.495965
Sales and service elementary occupations	91	Manual	0.027381
Labourers in mining, construction, manufacturing and transport	93	Routine	0.4486654

Source: Goos, Manning and Salomon, 2014. RTI index could be downloadable from the following website. https://www.aeaweb.org/articles?id=10.1257/aer.104.8.2509. The categorization is formed according to RTI Index and the explanations made by ILO http://www.ilo.org/public/ english/ bureau/stat/isco/isco88/.

Table A2 Occupation Categories (ISCO08)

Occupation	ISCO08 Code	Category
Chief executives, senior officials and legislators	11	Abstract
Administrative and commercial managers	12	Abstract
Production and specialised services managers	13	Abstract
Hospitality, retail and other services managers	14	Abstract
Science and engineering professionals	21	Abstract
Health professionals	22	Abstract
Business and administration professionals	24	Abstract
Information and communications technology professionals	25	Abstract
Legal, social and cultural professionals	26	Abstract
Science and engineering associate professionals	31	Abstract
Health associate professionals	32	Abstract
Business and administration associate professionals	33	Abstract
Legal, social, cultural and related associate professionals	34	Abstract
Information and communications technicians	35	Abstract
General and keyboard clerks	41	Routine
Customer services clerks	42	Routine
Numerical and material recording clerks	43	Routine
Other clerical support workers	44	Routine
Personal service workers	51	Manual
Sales workers	52	Manual
Personal care workers	53	Manual
Protective services workers	54	Manual
Building and related trades workers, excluding electricians	71	Manual
Metal, machinery and related trades workers	72	Routine
Handicraft and printing workers	73	Routine
Electrical and electronic trades workers	74	Routine
Food processing, wood working, garment and other craft and related trades workers	75	Routine
Stationary plant and machine operators	81	Routine
Assemblers	82	Routine
Drivers and mobile plant operators	83	Routine
Cleaners and helpers	91	Manual
Labourers in mining, construction, manufacturing and transport	93	Routine
Food preparation assistants	94	Routine
Street and related sales and service workers	95	Manual
Refuse workers and other elementary workers	96	Manual

Source: OECD, 2017, p.70, Figure 1.7. OECD makes ISCO08 into broad categories. ISCO 71, ISCO 83, ISCO 95 and ISCO 96 are taken differently by looking at the ISCO08-88 Correspondence (https://www.google.com.tr/search?q=ISCO+08+88+correspondence+tables+ILO&oq=ISCO+08+88+correspondence+tables+ILO&aqs=chrome..69i57.11139j0j9&sourceid=chrome&ie=UTF-8# Access: 12.7. 2017).