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SKILL BIASED TECHNICAL CHANGE AND WAGE INEQUALITY: EVIDENCE FROM TURKISH MANUFACTURING SECTOR

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İSTANBUL, 2021

GENERAL KNOWLEDGE

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ABSTRACT

SKILL BIASED TECHNICAL CHANGE AND WAGE INEQUALITY: EVIDENCE FROM TURKISH MANUFACTURING SECTOR

Although the wage inequality phenomenon has an evergreen debate in economics, its rebirth and salience, after the 1970s, is indebted to the upsurge of wage inequality in the USA. Since then, many efforts have been put to reveal the dynamics behind this increase, and Skill Biased Technical Change turned out to be the epicenter of the discussion. Skill Biased Technical Change or Appropriate Technology alters wages both between skill groups and within skill groups by favoring the labor involved via increased productivity. The main target of this dissertation is to display the effects of hypothetical and implied technology shocks in the form of skill biased technical change and general purpose technology on the Turkish manufacturing sector. Using HLFS data between 2004 and 2015, counterfactual wage distributions were constructed to understand what would have happened if the course of technology changes were different. Our contributions stem from the utilization of the counterfactual method within that framework, the newfangled quantification of skill biased technology by re-parametrization of the DFL method, and application to the Turkish manufacturing sector using micro-level data. The main results can be listed as followings: the effects of SBTC were greater than the effects of GPT; technology dimension was more structural and resistant against changes in wage than skill dimension in the manufacturing sector; there was a trade-off between the level of wage and wage inequality and finally, for different percentile groups, technology shocks generated rather varied results.

JEL Classification: J24, J31, L60

GENEL BİLGİLER

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ÖZET

BECERİ YANLI TEKNİK DEĞİŞİM VE ÜCRET EŞİTSİZLİĞİ: TÜRK İMALAT SEKTÖRÜNDEN BULGULAR

Her ne kadar ücret eşitsizliği olgusu, iktisat biliminde ölmeyen bir tartışma olsa da, 1970'lerden sonra, yeniden doğuşu ve öne çıkması, ABD'deki ücret eşitsizliğinin yükselişine borçludur. O zamandan beri, bu artışın ardındaki dinamikleri ortaya çıkarmak için pek çok çaba sarf edildi ve Beceri Yanlı Teknik Değişim tartışmanın merkez üssü haline geldi. Beceri Yanlı Teknik Değişim veya Uygun Teknoloji, artan üretkenlik yoluyla dahil olan emeği destekleyerek hem beceri grupları arasında hem de beceri grupları içinde ücretleri değiştirir. Bu tezin temel amacı, beceri yanlı teknik değişim ve genel amaçlı teknoloji şeklindeki varsayımsal ve örtük teknoloji şoklarının Türk imalat sektörü üzerindeki etkilerini göstermektir. 2004 ve 2015 yılları arasındaki HİA verilerini kullanarak, teknoloji değişimlerinin seyri farklı olsaydı ne olacağını anlamak için karşıolgusal ücret dağılımları oluşturulmuştur. Katkılarımız, bu çerçevede karşı-olgusal yöntemin kullanılması; DFL yönteminin yeniden parametrelendirilmesi vasıtasıyla beceri yanlı teknolojinin yeni ölçümü ve mikro düzeyde veriler kullanılarak Türk imalat sektörüne uygulanmasından kaynaklanmaktadır. Ana sonuçlar şu şekilde sıralanabilir:

SBTC'nin etkileri GPT'nin etkilerinden daha büyüktü; teknoloji boyutu beceri boyutundan daha yapısal ve ücret değişikliklerine karşı daha dirençliydi; ücret seviyesi ile ücret eşitsizliği arasında bir değiş tokuş vardı ve son olarak, farklı yüzdelik gruplar için, teknoloji şokları oldukça çeşitli sonuçlar meydana getirmişti.

JEL Sınıflandırması: J24, J31, L60

To my Family

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LIST OF ABBREVIATIONS

COL	: College
CPI	: Consumer Price Index
DFL	: DiNardo, Fortin and Lemieux (1996)
FDI	: Foreign Direct Investment
FSP	: Factor Specific Productivity
GE	: Generalized Entropy
GPT	: General Purpose Technology
HLFS	: Household Labor Force Survey
HSC	: High School
HS	: High Skilled
HSBC	: High Skilled Blue Collar
HSWC	: High Skilled White Collar
HT	: High Technology
ILO	: International Labour Organization
ISCO	: The International Standard Classification of Occupations
LS	: Low Skilled
LSBC	: Low Skilled Blue Collar
LSWC	: Low Skilled White Collar
LT	: Low Technology
MHT	: Medium High Technology
MLT	: Medium Low Technology
NACE	: Statistical Classification of Economic Activities in the European Community

n.e.c.	: not elsewhere classified
PS	: Primary School
R&D	: Research and Development
SBTC	: Skill Biased Technical Change
SSP	: Sector Specific Productivity
TURKSTAT	: Turkish Statistical Institute
VHS	: Vocational High School
w.r.t.	: with respect to

1. INTRODUCTION

Wage inequality has been experienced in a widespread manner all over the world, especially after the 1970s. Since then, although possible driving forces, considerably, are intertwined tightly, many efforts have been put forward to uncover the causes of such an increase in wage inequality. Seminal papers such as Aghion, Howitt and Violante (2003) and the series of papers by Acemoglu (1998, 2002a, 2002b, 2003a and 2003b) and literature reviews such as Aghion, Caroli and Garcia-Penalosa (1999), Hornstein, Krusell and Violante (2005), Chusseau, Dumont and Hellier (2008), and Förster and Tóth (2015) scrutinize the potential candidates that give rise to accelerate the wage inequality. Along with technological change, international trade, outsourcing, organizational change (Chusseau *et al.* 2008) and institutional changes, sectoral changes, tax structure, politics and demographic changes (Förster and Tóth, 2015) are regarded as the most prominent contributors of the recent wage differential across countries. However, technological change, more clearly skill biased technical change, is one of the grounds that the consensus has been built in wage inequality literature.

The underlying rationale is simply to presume that the technical change favors the skilled labor through the instrumentality of increasing their labor productivity or downward pressure on unskilled wages due to replacement and/or automation of tasks previously performed by the unskilled labor, which, in turn, deteriorates wage inequality in favor of skilled labor (Acemoglu, 2002b). To put it more explicitly, skill biased technical change notion is the theory of directed innovation affecting the productivity of factors differently either with substitution or complementarity between factors (Bogliacino, 2014). Nevertheless, the conventional wisdom of shift in new technology assists the skilled labor was argued by Acemoglu (2002b). According to him, the nineteenth and early twentieth centuries were characterized by skill-replacing developments due to increased supply of unskilled labor, that is to say, reserve army of unskilled workers, such as migration of unskilled labor from villages and Ireland to England, the agricultural revolution forced the rural population to settle down cities which made profitable to develop less-skill requiring technologies (Acemoglu, 2002b). Another view rooted in the nineteenth century can be drawn from the Luddite and Captain Swing riots because skilled artisans feared that their skills would fade away and became unemployed due to the replacement of weaving and spinning machines instead of themselves (Acemoglu, 2002b). Braverman (1974) and Marglin (1974) also put emphasis on “deskilling” in technical change as the fundamental motivation of technical advance is the simplification of tasks performed by artisans and “breaking them into smaller and less skill requiring pieces” (Acemoglu, 2002b: 3).

From this point of view, we need to ask why technological developments converted into skill biased technical change, hereafter SBTC, from skill-replacing technologies. The answer can be extracted from a large set of possibilities from a simple supply and demand framework of skilled and unskilled labor to the institutional framework or whether the technology is defined exogenously or endogenously. Our first aim is to find out how can technology be quantified through the help of reasons based upon theoretical literature. That procedure is crucial as there is no unequivocal data on technology in our dataset. Instead, we generate a hypothetical situation via re-parametrization of the counterfactual method proposed by Dinardo, Fortin and Lemieux (1996) that creates a newfangled way of acting as if workers are exposed to some kind of technology shock. For that purpose, we have three postulations serving as skill biased technical change and general purpose technology, hereinafter GPT. Within that framework, we impose high skilled attributes to the low skilled but they are still paid with respect to the wage structure of low skilled labor. Therefore, we give a technology shock to low skilled workers which increases their productivity as if they had experienced a SBTC. In other words, an answer to the following question can be found: what would be the wage distribution if the individual attributes had increased to high skilled manufacturing labor level while they had been paid according to the wage schedule observed in low skilled manufacturing sectors? Additionally, the answer allows us to construct a counterfactual wage distribution and we end up with two wage distributions: the original and the counterfactual. Comparison of them has the power to explain the effects of SBTC and also GPT on wage inequality. The same procedure is applied to high – low technology dimensions as well, but the general results are in harmony with skill dimension results. Nevertheless, kaleidoscopic impacts of technology shocks upon different wage dispersions are detected.

The plan of the paper is structured as follows. Chapter 2 is devoted to setting the scene for the theoretical framework of wage inequality, differentiation in skill premium induced by pure technological approaches with respect to the type of technology such as general purpose technology or skill biased technical change and also with respect to the spectrum of endogeneity of technologies are mentioned. Empirical literature including few Turkish cases is covered by Chapter 3 where especially our thesis contribution is connected with; at the same time, some benchmark studies are mentioned as well, investigating the US and the UK cases. In Chapter 4, data, potential proxies for technological advancement and their quantification are classified, and also inequality measures used in empirical analyses are introduced. Descriptive statistics such as wage distributions, wage ratios and entropy based inequality measures and their evolutions are the topics of Chapter 5. The main empirical methodology of counterfactual wage distribution and its re-parametrization are discussed in Chapter 6, which also includes the essence of our research: empirical results and statement of general patterns. Finally, we conclude with discussions of results and plausible policy implications in the last chapter.

2. THEORETICAL FRAMEWORK OF SKILL BIASED TECHNICAL CHANGE

To elucidate the theoretical pattern thoroughly, in the first instance we need to specify which elements of the economy would be influenced if a country moves from old technology to newer and higher technology. The conventional way of looking at aggregate technical change is the total factor productivity. However, it casts some doubt on the generalization of the specific effects. Aghion *et al*. (1999) enumerate counterarguments to questioning TFP method: first, the growth rate of residual can be explained by other factors such as capital labor ratio, age of capital, etc.; secondly, manufacturing and service sectors have different capital intensities and regarding their relative ratios as constant, gives a poor measure of technology; finally, technology parameter affects all labor types equally which biases technical change estimation. Bearing in mind those defects, technology morphs into a *Rorschach test*[1] in which you can see what you want (Bresnahan, 1999). By the same token, Hornstein *et al*. (2005) define this uncertainty with the analogy of the *black box*.

To account for a proper technology proxy, Aghion *et al*. (1999) propose more direct measures of technical change to test for the existence of SBTC such as computer related variables, patent number, and R&D expenditure. Besides, the relative size of the Information Technology sector is also used to quantify technology by Jorgenson (2001). The opposition of Card and DiNardo (2002) to the relative size of IT sector measurement stems from the idea that the influence of information technology related technical change on the economy may not be necessarily proportional to the size of the sector, and the IT sector embodies many different goods and services and this character makes it too simple to stand for technology.

Hornstein *et al*. (2005) point out that TFP is not capable to provide on the sources and the nature of technical change, especially in the case of the advent of microelectronics induced

[1] A psychological test depends on perceptions of inkblots patterns.

a sequence of innovations in ICT that have two significant features: sector-specific and factor-specific productivities.

Sector-specific productivity growth develops out of the rise in productivity that produces new capital equipment (investment goods), leading to a fall in the price of equipment by the reason of productivity improvements; therefore, equipment capital utilization in the production process increases simultaneously and since skilled labor is relatively more complementary to capital than unskilled labor, higher capital stock accelerates skilled wages relatively more than unskilled wages (Krusell, Ohanian, Rios-Rull and Violante, 2000). It is also called as capital-embodied technical change. Sector-specific productivity conduces to wage inequality by virtue of capital-skill complementarity. Estimations of Krusell *et al*. (2000) indicate that capital-skill complementarity is responsible for most of the variations in the skill premium throughout 1963-1992, where it nearly explains up to about 60% of skill premium in the USA.

Factor-specific productivity is related to changes in the productivity of individual productive factors, e.g., decomposing labor input into skilled and unskilled labor. Hornstein *et al*. (2005) emphasize that recent technological evolution has a quite asymmetric impact on the production structure, underpinning the skilled labor and inflating the skill premium. Katz and Murphy (1992) estimate an increase of over 11 percent per year in the relative factor-specific productivity of the skilled workforce.

The rest of this section explains SBTC from two different perspectives: exogenous SBTC and endogenous SBTC. The first subsection also underlines general purpose technology and three alternative hypothesizes linking supply and demand conditions in labor market to the speed of technological improvements. From the supply-side, steady-demand hypothesis and from the demand-side, acceleration hypothesis and the Nelson-Phelps hypothesis are mentioned. We conclude with endogenous SBTC by pointing out how it differs from exogenous counterpart.

2.1. EXOGENOUS SKILL BIASED TECHNICAL CHANGE

Skill biased technical change as a departure point to account for wage inequality requires appropriate identification of the nature of skill bias of technology. It could either be stimulated through exogenous factors as stated in this section or endogenous factors as listed in Section 2.2. However, the important distinction is that not the technical change itself but the skill bias of technical change should be exogenous or endogenous. For instance, Lloyd-Ellis (1999) constructs an endogenous technological change model while skill bias of technology still remains open to exogenous factors. The technological jumps and changes in the supply of and demand for skilled labor are three pertinent factors to illuminate exogenous SBTC.

2.1.1. General Purpose Technology

On the one hand, when the advancement of technology is analyzed from the perspective of supply and demand framework, better technology puts pressure on the demand for skilled labor and the skill premium deteriorates in favor of unskilled labor. On the other hand, due to an increase in returns to education, supply of skilled labor expands until reversing the wage inequality in favor of unskilled labor. Aghion *et al*. (1999) demonstrate that the adoption and implementation procedure of new technology might pave the way for an increase in wage inequality even in case of increased supply of skilled labor, through general purpose technology. General purpose technology (GPT) is a technological breakthrough that affects the entire economy, so new technology is non-rival and non-excludable.

According to Aghion *et al*. (1999), when a new technology is developed, almost no firms know how to exploit this new technology. All firms by themselves have to discover about it and learn from other firms' same experimentations. Therefore, at the beginning of the introduction of the new GPT, nothing happens at the economy at the aggregate level, but if firms continue their experimentations long enough, eventually a breaking point will be reached and area of utilization will spread over all the economy; therefore, during the transition period, since the number of firms using new GPT is not able to absorb all skilled labor, excess skilled labor will be employed at old GPT sector, earning wage as the unskilled labor (Aghion *et al*., 1999). For this reason, the labor market at this stage called as unsegmented. When the transition from old GPT to new GPT is completed, the demand for skilled labor accelerates with this spread, where its effect is analogous with the snowball effect and then, new sector becomes big enough to absorb all skilled workers with higher wages than unskilled labor market and the labor market is segmented (Aghion *et al*., 1999). Their simulations show that the number of sectors engaged in experimentation reached at peaks in 20 years and skill premium rose sharply after 21 years and continues to increase until the transition was completed where everyone ended up with the same skilled wage. By the same token, Galor and Tsiddon (1997) also build a similar perspective in their model.

2.1.2. Supply Side: Steady-Demand Hypothesis

Steady-Demand Hypothesis regards the rate of technological change as constant without any breaks in its trends. In other words, demand for skilled labor follows a smooth and secular upward trend. Exogenous factors affecting the skilled supply such as baby boomers, wars, or even educational policies are the main driving forces of changes in skilled and unskilled wage differential. This hypothesis is useful especially for the US case after the 1970s because when the demand for skilled labor is assumed to grow at an invariant pace which allows only tranquil deviations from its trajectory. The US did not suffer from high wage inequality before the 1970s as the rate of skill accumulation was in harmony with the skill biased technical change, and for this reason, an uptrend in wage inequality was rooted in the change in supply of skills. If the supply of skilled labor grows faster than SBTC, deviation of returns to skills will emerge as a source of inequality rather than the technological change itself.

Katz and Murphy (1992), Angrist (1995), and Card and Lemieux (2001) are some influential papers putting steady-demand hypothesis in the center of their analyses. Katz and Murphy (1992) investigate how supply and demand framework affected wages in the US manufacturing sectors over 1967-1987. Results display that changes in the wage structure differed severely throughout the decades: the college wage premium raised substantially in the 1960s, decreased in the 1970s, and raised again in the 1980s (Katz and Murphy, 1992). The difference between the relative earnings of the skilled labor and unskilled labor resulted from mainly different growth rates of the supply of college graduates, and additionally, fluctuation in the relative supply of skilled labor can partially be expressed by baby boomers entering the labor market in the early 1970s (Katz and Murphy, 1992).

Angrist's (1995) remarkable paper on the inclusion of skilled labor in the West Bank and the Gaza Strip during the 1980s when the establishment of the first university in 1972 is a good example of steady-demand hypothesis. Angrist (1995) indicates that Palestinian college skill premium to high school premium dropped from 40 percent to less than 20 percent when those locally graduated students entered the labor market since the absorptive capacity of skilled jobs was limited, such a wave in skills caused both skilled labor to be employed in unskilled jobs or even to be unemployed. Acemoglu (2002b) refers to Schiff and Ya'ari (1989) which manifests the severity of this situation, only one out of eight Palestinian graduates could find jobs in their professions.

Card and Lemieux (2001: 739) are "motivated by the observation that the college-high school wage gaps of different age groups have not moved together" after the 1980s for the USA, the UK and Canada until 1996. The main conclusion is that the college premium for younger workers in the US, and the UK increased considerably, while the premium for older workers almost remained unchanged in the 1970s levels (Card and Lemieux, 2001). Card and Lemieux (2001: 739) point out that structural transformation emanated from both "cohort-specific relative supplies of college-equivalent labor and steady rises in the relative productivity of college workers", through the agency of "imperfect substitution between similarly educated workers in different age groups." In this context, they attribute the rising college-high school wage gap to the steady increase in the relative demand for college graduates in the 1980s and 1990s. This impact is further consolidated by a simultaneous deceleration in the rate of increase in the relative supply of college educated labor.

2.1.3. Demand Side: Acceleration Hypothesis and Nelson-Phelps Hypothesis

Wage inequality induced by demand side has two important properties that are at odds with supply side view: new technologies are more complementary to skilled workers than unskilled workers and technological changes can have jumps in contrast to the constant rate of technological progress of steady-demand hypothesis. Therefore, lagged response of skilled labor supply cannot meet the demand originated from technological change in other saying demand for skilled labor. Rate of returns to skill, as a result, will change during that adjustment period. This alternative interpretation can be elaborated with two hypotheses: Acceleration Hypothesis and Nelson-Phelps Hypothesis.

Acceleration Hypothesis regards human capital as a separate factor of production, and the demand for human capital in terms of skills increases due to a rapid acceleration in the technological change which supports skilled labor (Acemoglu, 2002b). Therefore, there exists a trend shift from lower to higher wage dispersion as the rapid growth of technology creates a shortage of skilled labor, which immediately after increases the skill premium. According to this, the source of inequality is an upsurge in demand for skilled labor. In addition, Acemoglu (2002a) suggests that according to all acceleration theories, newer technologies are more complementary to skilled labor than unskilled labor. Welch (1970: 38) also mentions, “Technical change may not be neutral between skill classes. It may be that increments in the technology result in increments in the relative productivity of labor that are positively related to skill level.”

While Krueger (1993) does not directly aim at testing the validity of the acceleration hypothesis, she argues that the use of computers in workplaces has changed the wage structure substantially and workers who use computers have earned 10 to 15 percent more than regular workers. Between one-third and one-half of the rise in the return to education growth was ascribed to increased computer usage in the workplace between 1984 and 1989 (Krueger, 1993). Nevertheless, it is also discussed that this premium might come from unobserved skills. Berman, Bound and Griliches (1994), Autor, Katz and Krueger (1998), and Machin and Van Reenen (1998) are other examples supporting the acceleration hypothesis that search for evidence on increment in demand for skilled labor with the help of technical improvements.

Berman *et al*. (1994) analyze the shift in demand for skilled labor in the USA 450 manufacturing industries for 1979-1987 using investment in computer and expenditure on R&D as technological change indicators. Computer usage and computer related data are used by Autor *et al*. (1998) to account for technological change in 450 US manufacturing industries from the 1940s to 1995 while Machin and Van Reenen (1998) use R&D intensity for six OECD countries and the US at industry level for the period of 1973-1989. Nonproduction wage bill share is widely proxied for the skill upgrading. They have two common results: SBTC and the acceleration in demand shifts for more-skilled labor (not for new equipment) after the 1970s are the most critical factor increasing the relative demand for skilled labor. Krusell *et al*. (2000) argue, however, the demand for skills accelerated as a result of the decline in the relative price of capital equipment in the early 1970s. Hence, rather than the introduction of new technology, the price of capital equipment determines the level of wage inequality in terms of skill premium.

Greenwood and Yorukoglu (1997) link the rate of technological advances to the level of income inequality and productivity growth emphasizing the role of skilled workers in plant-wide learning by doing. Technological progress is embodied in the form of new machines and adoption of these new machines are costly; besides, the quality of new vintages transcends old vintages and reduces the initial level of knowledge of newly born firms (Greenwood and Yorukoglu, 1997). When there is a leap in the state of technology, new plant starts with a lower level of productivity; therefore, these firms should setup and learn to use new technology to improve technological know-how and since adoption involves a significant cost and skilled workers have an advantage at learning new blueprints, technology innovations assist at increasing the demand for skill, which is necessary to implement it (Greenwood and Yorukoglu, 1997). As a result, returns to skill and skill labor wages increase in the early phase of the technological revolution.

On the other hand, *Nelson-Phelps Hypothesis* gives more weight to innate skills rather than acquired skills through education. Nelson and Phelps (1966) divide the economy as conventional technology and leading edge technology, and the difference named as technology gap. Besides, technology gap is positively associated with skill premium. Greater technology gap is directly translated into greater skill premium, because the demand for skilled workers rises to adopt technology that is more productive. The wage premium for skilled workers does not only evolves out of their higher productivity vis-à-vis unskilled labor but also workers endowed with more skills, especially innate skills, are better able to cope with new technological transformation since turmoil generated from new technology affects their productivity less adversely; and also it is less costly to learn new skills that are required to use this new technology (Hornstein *et.al.*, 2005). Welch (1970:38) mentions Nelson-Phelps Hypothesis as these: "the productivity of education would be positively related to the rate of change in useful technology (the ability to change) and to the size of the technological gap (room for innovation). In this case, if the rate of utilization of technology is accelerating, or if the technology gap is growing, the returns to education will rise relative to other inputs."

Intergenerational earnings mobility dimension is added to the nexus of technological progress and wage inequality by Galor and Tsiddon (1997), who propose that earnings mobility governs the pace of technological progress whereas technological progress determines the evolutionary patterns of wage inequality and intergenerational earnings mobility. In their model, individual earnings or wages are determined by either parental specific human capital and/or individual ability. The invention of a new GPT attenuates sector-specific skill inherited from parents and also amplifies the mobility across sectors; and consequently, workers with high human capital starts to concentrate in technologically advanced sectors which use new GPT and their wages differentiate positively from the rest using old GPT (Galor and Tsiddon, 1997). As time passes by, the new GPT turns out to be more familiar and accessible, parental specific human capital starts to dominate again, and mobility across sectors falls, eventually inequality declines, and becomes more persistent (Galor and Tsiddon, 1997). In a nutshell, periods of inventions are closely related to inequality and intergenerational mobility and their directions are governed by the direction of output growth (Galor and Tsiddon, 1997). According to their results, technological development under the faster growth periods can increase inequality which is accompanied by the enhanced intergenerational mobility. On the other hand, it is also pointed out that the reduction in the concentration of ability in technologically advanced sectors lowers the likelihood of new GPT and slows future growth (Galor and Tsiddon, 1997). There is a cyclical nature of technological progress.

Caselli (1999) contributes from the perspective of technological revolutions by analyzing them according to their easiness of acquisition and introduces the concept of *de-skilling*. A new technological breakthrough comes up with new machines that are more productive. A worker can be either employed on a previously used or new machine. In each case, certain machine specific skill is needed to be obtained which by nature costly. Caselli (1999) differentiates technology -or revolution- with respect to their level of learning costs. Technological change is skill biased when the additional skills are costlier than the skills associated with pre-existing types of machines such as steam engine or information technology; but it is de-skilling when the new skills can be obtained at a lower cost than the skills required by pre-existing technology such as the assembly line (Caselli, 1999). The utilization of better machines is urgent and whoever learns the instructions faster will take the operation; therefore, fast learning workers, who have high cognitive ability, start using machines that are more productive and the slow learners remain attached to obsolescent and relatively unproductive machines. The revolution also gives rise to redistribution of capital from older technology to newer one, as the capital labor ratio in the former sector enjoys higher wages (Caselli, 1999). In the same vein, workers having high cost of learning will be punished by lower level of capital labor ratios and they will experience a decline in their wages. That wage differential will exist until a general adoption of the state of the art technology. On the other hand, if the country reaches the steady state point before the acquisition of instructions by all slow learners, the labor market remains segregated as skilled and unskilled, and wage inequality will persist (Caselli, 1999). All in all, he showed empirically wage inequality after 1975, related to increased capital labor ratios, was driven by skill biased technology revolutions.

Galor and Moav (2000) develop an exogenous model which is also endogenized later on. They propose that advances in technology boost the return to ability and at the same time creates a rise in the wage inequality both between and within groups of skilled and unskilled workers; and erodes some of the human capital of unskilled workers faster than those of skilled workers. Average wages increase for skilled labor but a temporary decline in average wages of unskilled labor is supervened on technological progress, which is followed by an escalation in educational attainment and relative but transitory productivity slowdown in the early phase of technological transition (Galor and Moav, 2000).

Aghion *et al*. (2003) develop a simplified version of Aghion and Howitt (1998) taking into account social learning. The general structure resembles the GPT adoption process mentioned in subsection 2.1.1. There are two types of technologies old and new technologies. Former is indifferent between skilled and unskilled labor whereas latter can only be acquired by skilled labor. In the long run, all workers will be able to adopt the new technology and turn out to be skilled but the rates of learning differ across individuals; however, in the transition period, the labor market is unsegmented, and different skill levels mostly do not acquire different wages, because the number of firms which can use the new GPT is too limited to absorb all skill supply (Aghion *et al*., 2003). In the second section of transition, the labor market may become segmented as the adoption of new technology widens the scope and all workers can work in jobs suited to their abilities and as a result, between group inequality increases, because these two wages are determined by two different labor market conditions (Aghion *et* *al*., 2003). So, the arrival of new GPT promotes the demand for not only observable skills but also unobservable skills. From within group inequality viewpoint, the new GPT is harmful because of two reasons. First, “dissemination of new GPT increases the market premium to those workers who are lucky enough to adapt quickly to new versions of the technology” and secondly “to the extent that new GPT generates a wave of secondary innovations that are closely related to one another, its diffusion especially benefits workers who are lucky enough to adapt quickly several times, who can profit from transferring recently acquired knowledge to the task of working with the latest innovations” (Aghion *et al*., 2003: 459).

Lloyd-Ellis (1999) constructs a general equilibrium model regarding wage inequality and technical change endogenously while skill biasedness is still exogenous. In his model, there is a minimum skill level for a new technology to be implemented by workers, who differ from each other with respect to skills they have and they need some time to be able to acquire the necessary ability to implement called absorptive capacity, which is limited by the current skill level of a worker (Lloyd-Ellis, 1999). When the rate at which new technologies are generated exceeds the rate at which they are absorbed because of increasingly intense competition for scarce, technologically mobile labor, in the short run, wage inequality increases even if technological change is not skill biased by nature (Lloyd-Ellis, 1999). This situation makes R&D costlier and also leads to cut down the rate of innovation. As the introduction of new technologies exceeds the absorptive capacity, the skill premium will continue to increase and technological changes will slow down. After all, enhanced inequality corresponds to diminishing rates of innovation, productivity and real wage growth; besides, in the long run, sufficiently low skill premium is the only mechanism to accomplish high rates of technical change (Lloyd-Ellis, 1999).

The Nelson-Phelps hypothesis has the ability to uncover why the skill premium, in terms of college, decreased simultaneously that the wage gap within college graduates increased in the 1970s. The rationale behind this is explained by Hornstein *et al*. (2005: 30) stating that “in the early phase of IT diffusion in the 1970s only educated workers with high ability adopt. Naturally, this higher return to ability increases within-group inequality. The contemporaneous acceleration in the growth of the supply of educated labor, due to exogenous factors, explains the relative fall in the average wage of college graduates.” Violante (2008) also supports that quotation by expressing the increase in the skill premium is transitory when the Nelson-Phelps hypothesis holds and as workers get used to new technology or blueprint, wage dispersion, which is created by increased demand for skilled labor caused by technology shock, vanishes away at all.

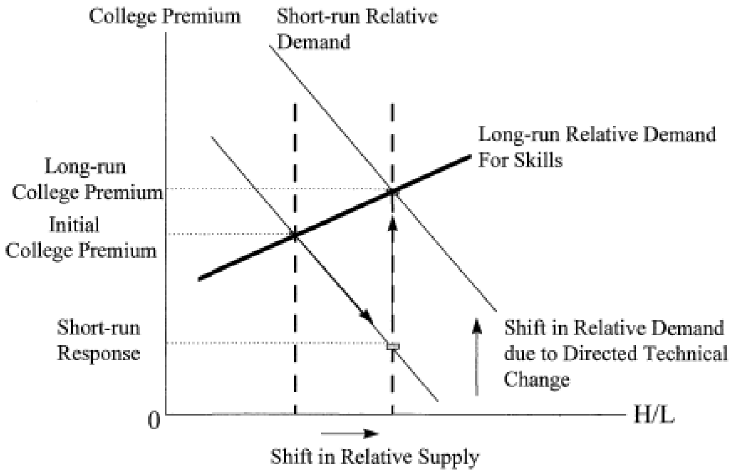
2.2. ENDOGENOUS SKILL BIASED TECHNICAL CHANGE

The main determinant of why researchers and firms try to introduce new machines, goods, or technologies is the basic instinct of entrepreneurs: capturing profits which act as an incentive to develop new techniques. From this point of view, the decision of which trajectory, new technologies follow, is solely taken endogenously. Therefore, in this section, that strand of the literature will be examined briefly.

Endogenous SBTC is constitutively different than previously mentioned theories because while exogenous SBTC assumes technical change to be skill biased by nature such as a jump in technology increased the demand for skills owing to exogenous factors or supply of skills changes due to again exogenous reasons e.g. wars, baby boomer, educational policies, etc.; endogenous SBTC theory is inspired by mainly Schumpeterian growth theory, linking the type of technology developed and adopted to profit incentives and opportunities. This setup is also called as *demand push hypothesis* where the idea springs from the increase in skilled labor supply causing firms to develop new technologies complementary to those skills. Endogenous SBTC literature almost wholly is incarnated by a series of seminal papers of Acemoglu (1998, 2002a, 2002b, 2003a and 2003b) and also Kiley (1999).

Acemoglu (1998: 1056) highlights the significance "that new technologies are not complementary to skills by nature, but by design"; thus, the direction of technical change is driven endogenously. His model produces a final good manufactured by two intermediate goods: one good is produced by firms using certain types of machines with skilled workers and the other good is produced by firms using certain types of machines with unskilled workers. New technologies come from the efforts to improve these intermediate goods through innovations. The decision of which sort of skilled or unskilled goods should be improved depends upon their relative market size; besides, innovation can be complementary to both skilled and unskilled labor, because experiment to develop a new technique requires a fixed cost and its return bases on which type of labor dominates (Acemoglu, 1998). The *market size effect* encourages innovations for the more abundant factor. If the supply of skilled labor increases as in the 1970s, the market for skill-complementary gets larger and the investors see an opportunity to capture profits to develop more skill-complementary technologies; therefore, the fundamental innovative stimuli are barely profitability consideration (Acemoglu, 1998). In addition to that, the impact of an increase in the supply of skills has a non-linear effect on wage inequality: firstly, the skill premium decreases in the short run due to a rise in the supply of skills because of the substitution effect; secondly, a higher fraction of skills in labor redirects research activities to in favor of skill-complementary technologies (Acemoglu, 1998). The directed technological change, thereafter, increase the relative demand for skilled labor in the long run through the *directed technology effect*, thereby worsens wage inequality in terms of the skill premium increment and long run level of skill premium hinges on whether substitution effect or directed technology effect dominates as shown in Figure 2.1. In the first phase, the economy moves along the short-run relative demand according to substitution effect because there is a large inflow of skilled labor which is indeed not expected and the technology has not time to adjust that supply of skill rise. At the end, the skill premium declines. Nevertheless, the overall effect depends on how directed technology effect shifts the relative demand. In the second stage, technology begins to adjust to the new state and the directed technology effect predominates the substitution effect, leading an increase in the skill premium.

Figure 2.1: Directed Technical Change and Dynamics of College Premium

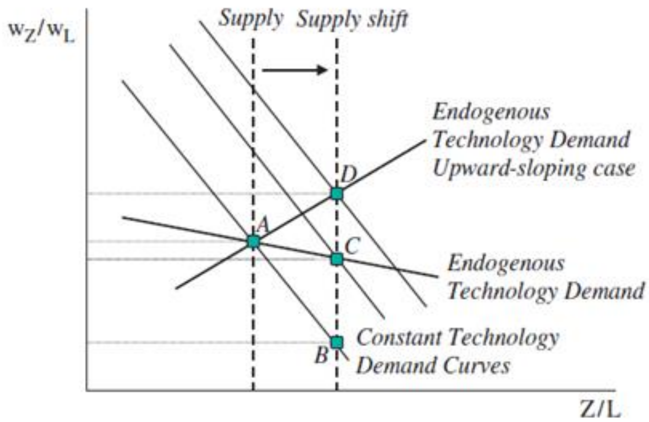


Source: Acemoglu (1998: 1057).

First models of SBTC mentioned in section 2.1 assume new technology is skilled biased and due to learning cost is low for skilled labor, they benefit first and later unskilled labor can get some return from a new variety. However, Kiley (1999) builds up a model asserting the contrary of new technology is inherently skill biased. Search for new efficient technologies or machines is consciously taken decision and research efforts directed to improve the productivity of inputs (Kiley, 1999). For example, a new sort of computer with high artificial intelligence can be either skilled biased technology or unskilled biased technology because it simply replaces controllers. At the end, it will be biased towards the factor ensuring the largest return. The supply factor determines skill-complementary or labor-complementary technology and higher skilled labor calls for skill-biased technology and skill-biased technology will stimulate the demand for skilled labor (Kiley, 1999).

Acemoglu (2002a) has basically two new concepts different than his previous work: price effect and innovation possibility frontier. The *price effect* means that even in case of expensive factors in production can create incentives to rapid technological improvement, since goods produced with scarce factors have a higher price, more innovation will be directed at these factors (Acemoglu, 2002a). Within this framework, there is a fierce competition between two forces: the price effect and the market effect. The price effect supports scarce factors while the market size effect favors abundant factors. Acemoglu (2002a) shows that the elasticity of substitution between these factors determines the relative strength of the effect; and if the elasticity of substitution is low (high, especially a certain threshold between 1 and 2), the price effect (the market size effect) dominates. In the absence of endogenous technical change, as shown in Figure 2.2, an increase in the supply of skill moves the equilibrium point from A to B and if the elasticity of substitution is different than 1, that increase conduces to biased technical change to point C where the constant technology curve is stepper than the endogenous technology demand curve (Acemoglu, 2002a). If the elasticity of substitution is large enough, biasness in technology invalidates the substitution effect and increase the relative return to that factor which has become more abundant; so, increasing returns to scale in the R&D induced to an upward sloping long run relative demand curve: once the new machine or technique is invented, it can be adopted by other workers due to the nonrivalry (Acemoglu, 2002a).

Figure 2.2: Constant Technology and Endogenous Technology Relative Demand Curves



Source: Acemoglu (2002a: 784).

Acemoglu (2003a) develops a model that incorporates the impact of technology and trade on wage inequality while treating the skill bias of technology endogenously. According to the model, an increase in demand for skills might result from two sources: trade and technology. When the number of skilled workers increases, the market size effect, there is a room for skill complementary technology and profit opportunities created in that part of the economy encourages firms to invest in this sector, finally directing technical change at them. As a result, new technology will become skill biased and the demand for skilled labor will have a higher rate of return. Trade is a catalyzer in that framework in contrast to standard models, because of abolishing boundaries across skilled labor and skill premium can increase not only in developed or frontier countries but also least developed countries which liberalize their trade (Acemoglu, 2003a). As the skill premium increases, wage inequality is assumed to deteriorate. Before open trade, least developed countries, to some extent, can only use local technologies which are less skilled biased due to the abundancy of that production factor and once the trade is opened, those countries will import more advanced technologies and domestic prices will be set with respect to world supply (Acemoglu, 2003a). Besides, the difference from Acemoglu (1998) is two-fold: first, Acemoglu (1998) model is a closed economy model while in Acemoglu (2003a: 201) considers "the equilibrium skill bias of technology is determined at the world level" within a multicountry model; second, the latter paper includes the international trade in its setup with the demonstration of openness-led skill biased technological change.

The epicenter of exogenous-endogenous skill biased technical change debate is grounded on the sensitivity and necessity of direction in technical change. Acemoglu (2002b: 42) discusses as pointing out that "exogenous technical change maintains that technical change is often skill-biased, endogenous technical change suggests that the new technologies should be skill-biased" when skilled labor is the abundant factor. Put it differently, endogenous skill bias theory predicts that the future path of technical change should be closely tied to the path of supply of skills while exogenous skill bias theory has no clear cut reason to further increase or decrease in the skill bias nature of new technologies (Acemoglu, 2002b). Apart from all these, the theoretical structure is built for frontier countries where new technologies are generated. Skill biased framework dealing with least developed countries depends on Acemoglu and Zilibotti (2001) where productivity differences between the North and the South are studied. The North can create *appropriate* technologies suitable for unskilled or low skilled labor since skilled labor is the scarce production factor in those countries. That offshoot has put some support behind technological change and returns to skill nexus for the South.

3. EMPIRICAL LITERATURE

Prominent contributions from the empirical side at the micro level are various and some of them have been already mentioned in Theoretical Framework Section to support the relevant theory. Therefore, this section is mostly devoted to Turkish examples which are, in fact, not voluminous. On the other hand, we include Berman *et al*. (1994), DiNardo *et al*. (1996), Haskel and Slaughter (2001), Card and DiNardo (2002), Wheeler (2005), Lemieux (2006), Hijzen (2007), and Autor, Katz and Kearney (2008) as benchmark studies due to their scope and novelty.

Besides Krueger (1993), Berman *et al*. (1994) also studied how computers changed the demand for skilled labor changed from 1959 to 1987 in 450 industries of the US manufacturing, using four-digit industry level microdata. Workers were classified as production (skilled) and non-production (unskilled) workers and changes in the non-production labor's share in wage bill was seen as a proxy for change in demand for skilled labor, while technology was estimated by share of investment in computers to total investment and expenditures on R&D to sales. The 1980s were characterized by skill upgrading arising out of SBTC and most of the increase in the relative demand for skills stemmed from within rather than between industries Berman *et al*. (1994).

DiNardo *et al*. (1996) handled wage inequality from an institutional perspective by introducing a pioneering semiparametric approach that draws counterfactual wage distributions over 1979 - 1988 for the US. According to their results, increased wage inequality, especially at the lower tail, in the 1980s took its source from a change in the institutional structure, largely fall in the real minimum wage and de-unionization, emphasizing the importance of institutional framework as well as supply and demand conditions in the labor market. Almost one-third of the rise in residual wage inequality was indebted to a real decrement of the minimum wage.

Haskel and Slaughter (2001) analyzed the interactions between trade, technology and wage inequality for 135 UK manufacturing industries at three-digit at 5-year intervals. Labor data was divided into manual (unskilled) and non-manual (skilled) employees. The ratio of non-manual wage to manual wage ratio was taken as an indicator for wage inequality. TFP growth was used as a proxy for technical change while changes in product prices were taken as a trade measure. Besides, average innovation per industry at two-digit and changes in the computerization were added to possible determinants of TFP. On the one hand, when trade and technology were regarded as exogenous, changes in prices were the main dynamics behind the rise in inequality in the 1980s, not TFP. On the other hand, when trade and technology were endogenized, skill premium increased due to factors such as tariff, changes in OECD prices and industry concentration.

Card and Dinardo (2002) presumed computer usage as an indicator for technology and searched for the dynamics behind the changing nature of the US wage inequality. Technology upgrades could affect a specific skill group either who had ability to use computers or directly highly skilled workers. The standard deviation of aggregate wages, the wage gap between the top and the bottom deciles as overall wage inequality, and residual inequality generated from a simple regression on sets of variables such as race, education and experience were used as main indicators. They stated that wage inequality in the US was an episodic event because, although during the 1990s, computer technologies continued to be more widespread, wage inequality entered into a stage of tranquility. SBTC explained less than 1/5 of the wage inequality and decrease in real minimum wage was seen as an important ingredient of wage inequality.

Wheeler (2005) examined the relationship among inequality, worker education levels, and workplace computer usage using a sample of 230 US industries between 1983 and 2002. Within-industry and between-industry wage inequalities were constructed through variance decomposition. The increase in wage inequality was explained primarily by within-industry variations which accounted for 75 to 80 percent for all years. Then, log hourly wages were regressed on a vector of variables where computer usage was designed as a direct measure of SBTC, and the college share corresponded as an indirect measure. At the end, SBTC was found as one of the significant factors for the increase in wage dispersion.

Lemieux (2006) ended up with supporting findings for the role of decrease in the real minimum wage and failed to find pieces of evidence on SBTC during the 1980s high wage inequality era. Residual wage inequality for 90-10, 50-10, and 50-10 percentiles were used and skill was replaced with education and labor market experience. According to Lemieux (2006), the SBTC hypothesis is valid only under a restrictive assumption: technology was skill biased in the 1980s but in the remaining period technology was naturally in favor of unskilled workers.

Hijzen (2007) studied the effects of outsourcing and technology on wages using three-digit manufacturing data for the UK for the period 1993–98. The contribution of the paper is that it explicitly addressed the relative importance of factor and sector bias (or the direct and indirect effects) of SBTC and outsourcing. "The sector bias captures the relative cost-saving effect across industries, while the factor bias captures relative changes in total factor use" Hijzen (2007: 189). The methodology employed in the empirical part was the two-stage mandated wage regression. Workers were classified as skilled or unskilled by ranking occupations with respect to their qualifications, training, skills, and experience. Total intermediate purchases times openness was used as a proxy for outsourcing and SBTC was measured by R&D intensity. Hijzen (2007) found no significant effect of R&D on skilled workers; however, unskilled wages fell by 0.17% per year as wage inequality increased by 1.7% annually. Decomposing the total effect of SBTC into its respective factor and sector bias components indicated that factor bias was slightly more important than sector bias.

Another approach in understanding of wage inequality depends directly on the source. *Revisionists* underline changes in the demand for and supply of skilled labor as the main determinant of changes in wage inequality; therefore, increments of wage inequality are taken as a one-time event caused by non-market forces such as a decline in the real minimum wage (Autor *et al*. 2008). On the other hand, the *traditional* approach presents sustained growth of skill demand particularly with computerization, and wage inequality is governed by the response of skill supply. Autor *et al*. (2008) investigated the US wage inequality case for 1963-2005 through the angles of both traditional and revisionist approaches. College employment was regarded as skilled labor while high school employment as unskilled, the ratio of skilled to unskilled was regarded as a technology proxy. Wage inequality was studied by 90/10 log wage differential, upper (50/10) and lower (50/10) tail differentials, between and within (residual) group wage differentials. Their results support the SBTC hypothesis and manifested that the wage distribution was vulnerable to changes in skill demand. As opposed to revisionist, Autor *et al*. (2008) found weak evidence on "episodic event" claim of wage inequality acceleration in the US. Wage inequality, indeed, had continued to grow during the 1990s to the end of the period and unlike the revisionist, minimum wage was eliminated as a proximate cause of the surge in inequality because the majority of wage inequality was induced by upper tail (Autor *et al*., 2008).

There is also another approach to skill content of technological change flourished by Autor, Levy and Murnane (2003). They searched the effect of computerization on the demand for skill but in terms of cognitive skills rather than bare educational, production – non-production workers or blue – white collar distinctions in the US from 1960 to 1998. The demand for routine cognitive tasks found to be decreased while the demand for non-routine cognitive tasks increased during that period. Therefore, intensive usage of computers in workplaces was a substitute for labor who worked on cognitive and manual tasks; however, it was complementary for labor who worked on non-routine cognitive tasks (Autor *et al.*, 2003).

On the other hand, SBTC and wage inequality nexus in Turkey is a quite intact field; we can argue that wage inequality literature in Turkey is rather voluminous. Wage studies generally interest in overall wage inequality and gender wage gap. There are some studies as well which capture different facets such as informal and formal wage gap (Tansel, 2005) and wage curve derivation (İlkkaracan, Levent and Polat, 2013).

İlkkaracan *et al*. (2013) addressed the negative relationship between real wage level and local unemployment rate using HLFS. They separated local unemployment levels into three educational categories as less than secondary, secondary and tertiary to stand for job market skill. Lower and upper ends of the wage curve had high elasticities and high elasticity at the lower end was explained with downward rigidity (İlkkaracan *et al.*, 2013). Wages in that part of the wage curve was already near to subsistence level and did not have enough room to move downward and additionally, high elasticity at the upper-end was clarified as that high skilled workers were safe from unemployment danger. Dervişen (2011) is another study that estimated the elasticity of substitution between skilled and unskilled manufacturing labor, showing that the Turkish manufacturing sector on average experienced unskilled labor augmenting technical change. Due to the lack of wage data, skilled wages were estimated according to production and administrative workers assuming unskilled labor was paid minimum wage (Dervişen, 2011).

Gender wage gap literature is ampler with papers such as Kara (2006), İlkkaracan and Selim (2007), Aktaş and Uysal (2016), and Tekgüç, Eryar and Cindoğlu (2017). Oaxaca decomposition method was used by Kara (2006), İlkkaracan and Selim (2007) and Tekgüç *et al*. (2017) They found evidences on gender discrimination against females with different datasets. Kara (2006) used Turkish Household Expenditure and Income Survey while İlkkaracan and Selim (2007) employed Employment and Wage Structure Survey and both studies were conducted for year 1994. İlkkarancan and Selim (2007) also mentioned that gender wage gap had a tendency to decelerate when occupation and industry selection of females were controlled. Tekgüç *et al*. (2017) with Household Labor Force Survey between 2004 and 2011, is separated from previous examples by taking into account of asymmetry in labor force participation in tertiary education in favor of female labor. Disaggregation of data into more homogenous groups resulted in that aggregated data had prone to demonstrate female over-qualified. Aktaş and Uysal (2016) utilized quintile regression analysis for the same issue using the 2006 Wage Structure Survey. At the lower tail, wage gap was too negligible and when education was controlled wage gap increased, although controlling industry and occupation acted in the opposite direction. They also conducted Machado-Mata decomposition and a large part of gender wage gap was attributed to differences in returns.

Tansel and Bodur (2012), using Household Income and Consumption Expenditure Survey for 1994 and Household Budget Survey for 2002, investigated male wage inequality through a Mincerian wage equation estimated by quantile regression. Education was a noteworthy contributor to wage inequality for both within and between wage groups; however, from 1994 to 2002, between group wage inequality recovered compared to within counterpart (Tansel and Bodur, 2012). Daş and Doğruel (2017) followed Tansel and Bodur (2012) methodology and extended coverage to 2002 and 2011. Despite an amelioration in 2002, overall wage inequality increased in 2011, and de-unionization was emerged as a wage equalizer factor.

Bakış and Polat (2015) utilized the DFL technique for Turkey; however, their approach to this method was different than this dissertation. Counterfactual wage distributions were constructed in accordance with DiNardo *et al*. (1996), attributing specific year's characteristics to another year. They studied wage inequality from 2002 to 2010 in Turkey with HLFS using overall and residual wage differentials of 90/10, 50/10, and 90/50. The supply and demand framework proposed by Katz and Murphy (1992) was employed to identify determinants of wage inequality. Bakış and Polat (2015) divided the period into 2002-2004 and 2004-2010 and rise in the supply of highly educated workers to poorly educated workers pertained to 2004-2010 period and highly educated workers' wages were in acceleration. On the other side, the supply of highly educated workers relative to poorly educated workers was constant while poorly educated workers' wages were in acceleration. Since the supply and demand framework was insufficient in finding the source of inequality, DFL counterfactual analysis and Juhn, Murphy and Pierce (1993) decomposition method were implemented, and supporting results for the revisionist approach were obtained. The real minimum wage hike in 2004 was responsible for the observed decline in the wage gap between 90/50 and 50/10 dispersions. Pelek (2013) also confirmed using the DFL method that minimum wage rise in 2004 was the leading factor in the reduction of wage inequality between 2003 and 2005.

Popli and Yılmaz (2017) used the same dataset for the same period with the same wage gaps as Bakış and Polat (2015), but differed in decomposition method and addition of occupational dimension as routine, service and abstract into the framework. Popli and Yılmaz (2017) accommodated a boost in the supply of educated labor to compulsory education and the increase in the number of universities. As a result of supply changes, 90/50 and 50/10 wage inequalities decreased; at the same time, the decrease in 90/50 wage inequality was relatively lower than the decrease in 50/10 wage inequality. According to Firpo, Fortin and Lemieux (2009) decomposition, Popli and Yılmaz (2017) attributed the decline in the lower tail wage inequality to changes in returns for education and experience while changes in returns to routine jobs were the main source of the decline in the upper tail wage inequality.

Aksoy (2009) is one of the earliest studies establishing a relation between technology and demand for skilled labor in the Turkish manufacturing sector at four-digit between 1995 and 2001. Two models with respect to skilled labor definition were estimated by fixed effect panel data. Share of investments in computer and software in output was selected as the technology variable. In the first model, the share of nonproduction workers was regarded as skilled labor whereas the share of production workers as unskilled labor, but the technology was insignificant. In the second model, the share of technical worker was taken as skilled labor and in this way, technology was weak but significant, confirming SBTC.

Meschi, Taymaz and Vivarelli (2011) paid particular attention to trade openness by reconciling with technology adoption and changes in skill demand, over 1980-2001 at two-digit firm level data from Annual Manufacturing Industry Statistics. Besides, input-output tables were also employed to generate import shares variable. Their main target was to figure out what was the role of trade and technology in skill upgrading in the workplace. Due to lack of concrete skill distinction in data, they followed similar categories as: production workers as unskilled and administrative workers as skilled. First, Meschi, *et al*. (2011) tried to uncover whether augmentation in demand for skills in the form of aggregate cost share of skilled workers, originated from employment reallocation across industries or directly from skill upgrading within industries. Using Berman *et al*. (1994) decomposition technique, the aggregate cost share of skilled workers increased by 14.8% during the period and 88% of that rise was rooted from within industry component. After that, as net technology importer character of Turkey, trade openness was expected to amplify inequality via increasing the demand for skilled labor. A cost share equation was estimated by dynamic panel data to test effects of four factors on skill demand: export, import, FDI and technology transfer through foreign patent and licensing; and all factors had significant impacts on demand for skilled workers and additionally, significant import shares proved the validity of skill enhancing trade hypothesis besides SBTC (Meschi *et al*. 2011). *Skill enhancing trade hypothesis* claims that openness in trade makes use of high technologies of developed countries by developing countries, and through imported embodied technology, the demand for skilled labor escalates (Meschi *et al*. 2011). Another transmission mechanism was put forward, regarding this hypothesis, through spillovers from import and FDI inflows by Coe and Helpman (1995) and Coe, Helpman and Homaister (1997).

Meschi, Taymaz and Vivarelli (2016) used Annual Manufacturing Industry Statistics over 1992-2001 to analyze similar issues as in Meschi *et al*. (2011) by incorporating employment and wage trends of skilled and unskilled workers. The skilled part consisted of white-collar administrative workers and blue-collar production workers substituted for unskilled workers. In addition to that distinction, Meschi *et al*. (2016) included investment in both imported machinery and equipment and domestically produced machinery and equipment. They reported shreds of evidence on the validity of SBTC in Turkey, and furthermore, although FDI gave rise to *absolute* skill bias, other variables such as R&D, export and technology transfer from abroad suggested *relative* skill bias. Meschi *et al*. (2016: 657) state the difference between absolute and relative skill bias as “a change in technology (or trade) would be absolutely biased toward skilled labor if it increases the number of skilled workers, while decreasing that of unskilled ones. A relative skill bias would instead appear when the coefficients for both skilled and unskilled workers are positive and significant but differ in their magnitude, with the coefficients for the unskilled workers being significantly lower.”

A recent study, Filiztekin (2020), explored the income inequality trends in Turkey from 2003 and 2015, including all sub-groups. Although instead of wage inequality, Filiztekin (2020) dealt with income inequality, his research used two other datasets, Survey of Income and Living Conditions, and Household Budget and Expenditure Survey, enabling us to compare some parts of our primary results, besides, time scope is nearly same with this thesis. Using percentile ratios, he revealed that there are two different episodes: 2003-2007 and 2008-2015. In the first period, the median wage grew faster than the 90th percentile wage but the median wage further diverged from the 10th percentile wage; however, that picture was reversed for the second period and an increase in university graduates with high earnings was seen as the main driving force of deterioration in wage distribution after 2007 (Filiztekin, 2020).

4. DATA AND METHODOLOGY

In the first part of this section, we introduce HLFS datasets and explain how they are converted into a more favorable way to make them tractable. This procedure includes principally the transformation of the real hourly wage variable and the establishment of consistency in variables among different years. The next subsection covers the identification of skills and technology and their grouping methods. In a broad manner, both skill and technology are categorized into four different subdivisions. Skill composes of high skilled white collar, high skilled blue collar, low skilled white collar, and low skilled blue collar, using occupation types at ISCO08 at one-digit. Then, instead of the collar feature, we divide skill into high skill and low skill. By the same token, technology is aggregated into high technology and low technology using four technology levels based on NACE Rev.2 at two-digit manufacturing industries information: high technology, medium high technology, medium low technology, and low technology. Inequality measurements and particularly, Theil entropy index are introduced in the last subsection.

4.1. DATA

The datasets available in Turkey has not a direct answer to the question of how does technological progress in terms of skill-bias affects wage inequality. We have two options: individual level data or firm level data. Due to the restrictive situation of firm level data, which is published under the name of A-group micro data, only available at data research centers, Covid-19 hinders us to utilize that perspective. Therefore, the very same question is tried to be answered using individual level data of Household Labor Force Survey. Before going a step further, we need to bear the caveat of the whole analyses throughout this thesis is made for male inequality to stay in harmony with the general tendency in literature. Therefore, when wage inequality is seen, it means male wage inequality. Empirical literature usually adds gender dimension either as a separate gender variable or separately. However, as we move to more detailed fragmentations that require much more fined away data, the number of observations decreases seriously. As a consequence of this drawback, a general overview of wage inequality in the Turkish manufacturing sector is scrutinized for males. To put a finer point on it, we have 12291 and 3264 data in 2004 for males and females, respectively. On the other hand, the number of observation in each cell that indicates the interaction of technology and skill level decreases even further than male counterparts (i.e. high skilled white collar females working at high technology is only 26 in 2004), see Table A3 and Table A4. In order to refrain from potential biases, female data removed.

To start with, raw data of HFLS should be refined to be able to make it well-behaved. The real hourly wage is calculated by standard procedure. Full time wage earners who report a positive income in the reference week are only kept at ages between 15 and 65, while working hours less than 8 or more than 84 are dropped. “Wage earners who did not work in the survey month and/or did not report positive income for that month” are discarded (Tansel and Bodur, 2012: 110). Additionally, if a person is self-employed or works temporarily/unregularly is not taken into account. Therefore, only those who have a regular job and earns a wage in exchange for their labor are kept. Second job holders are also discarded, so 0.1% and 4% of the data are removed during tailoring, in 2004 and 2015, respectively.

To deal with outliers, 1% of top and bottom at the wage distribution are trimmed. HFLS reports monthly wages and to construct real hourly wage, weekly work hours and hourly real wage are constructed through several steps. Total monthly hours worked is estimated by multiplying reference week work hours with 4.33. The nominal hourly wage is estimated by dividing monthly nominal wages with total monthly hours worked in the main job. In the questionnaire, question 69[2] asks for monthly nominal income instead of a *wage*. Although income and wage are different semantically, the question involves “total net income from your main job in the past month” and only workers who are “paid, salaried or casual workers” having “regular job” are taken into consideration; thus, “income” turns out to be “wage” at the same time. Besides, “monthly net income” includes periodic bonuses, premiums, etc. Finally, the nominal hourly wage is deflated by the Consumer Price Index with the 2003 base year to obtain the real hourly wage.

[2] In recent years, this question has been asked as question 72.

During this research, readers should keep some issues in mind. Information of the reference months in the HFLS is not reported, thus real wage is derived using yearly averages of CPI[3] rather than monthly CPI. The next issue is the continuity of the HFLS. After the 2014 survey, TurkStat writes a note about comparableness of former surveys saying that "in the labor force survey, the new regulations reflecting the differences in survey design, field application, job search duration, projection, and administrative division caused the indicators obtained to differ from the data sets before 2014 and eliminated their comparability." Another question is related to the number of employees firms have. For all survey years, a 50-employee threshold is constant but again, after 2014, an ambiguity comes in sight as the addition of "unknown, but more than 10 workers" and "unknown, but less than 11 workers" in 2014 and "unknown, but more than 10 workers" in 2015 to the options. 401 and 49 individuals[4] are omitted respectively for both years in analyses reported at Section 5 and 6[5] because of the uncertainty in firm size.

We also identify five educational categories as follows: below primary school, primary school, regular high school, vocational high school and college graduation. Illiterate and less than 8 years of schooling are counted in below primary school to find a common ground among related question in HLFS across years. The primary school includes at least 8 years schooling. The college includes college, faculty, or upper education.

4.2. QUANTIFICATION OF SKILL AND TECHNOLOGY

Wage inequalities are delved into different aspects in our analyses rather than implementing a holistic approach. The lynchpin of that perspective relies on two facets: skill and technology. Those are chosen to reflect the skill bias structure based on some firm theoretical reasons derived from Section 2. A detailed explanation of how technology is treated to reflect skill biased direction is left to Section 6.

[3] CPIs are 2003=100, 2004=108.6, 2005= 117.48, 2006=128.76, 2007=140.03, 2008=154.66, 2009=164.32, 2010=178.40, 2011=189.95, 2012=206.84, 2013=222.33, 2014=242.02, and 2015=260.59.

[4] 0.027% in 2004 and 0.0033% in 2015.

[5] Counterfactual wage distribution requires logit estimation for the construction of weights and firm size is taken as one of the potential explanatory variables.

Skill perspective is added in sense of two traits: occupations and education. HLFS reports two-digit occupation data in terms of ISCO classification versions 88 and 08. ISCO88 is claimed to be outdated because of the significant improvements in technology and subsequent changes in the boundaries of occupations and skill dimensions, which are inevitable. Therefore some categories were merged, split, or moved to capture changes in the labor market.[6] Although HFLS changed the version of ISCO from ISCO88 to ISCO08 in 2012, such a transformation stops being a problem since we aggregated higher degree occupation categories into one-digit occupation level and changes at the first digit remain considerably limited. In addition to that, as we try to capture skill perspective, replacement of an occupation from one skill level to another is still reasonable and moves in concert with changes in the skill level of the occupations. See Appendix Table A1 for two-digit ISCO08.

Following the European Working Conditions Survey methodology, nine occupation categories are consolidated into four main categories according to skill levels and collar types as seen in Table 4.1.

Table 4.1: ISCO Classification to Skill Specification

<table>
<tr><td>Managers</td><td rowspan="3">High Skilled White Collar</td><td rowspan="5">High Skilled</td></tr>
<tr><td>Professionals</td></tr>
<tr><td>Technicians and Associate Professionals</td></tr>
<tr><td>Skilled Agricultural, Forestry and Fishery Workers</td><td rowspan="2">High Skilled Blue Collar</td></tr>
<tr><td>Craft and Related Trades Workers</td></tr>
<tr><td>Clerical Support Workers</td><td rowspan="2">Low Skilled White Collar</td><td rowspan="4">Low Skilled</td></tr>
<tr><td>Services and Sales Workers</td></tr>
<tr><td>Plant and Machine Operators and Assemblers</td><td rowspan="2">Low Skilled Blue Collar</td></tr>
<tr><td>Elementary Occupations</td></tr>
</table>

Source: International Labour Office.

"*Skill level* is defined as a function of the complexity and range of tasks and duties to be performed in an occupation." (International Labour Office, 2012: 11). This report also mentions

[6] For a detailed list of occupational changes refer to International Standard Classification of Occupations ISCO08 – Vol I – Structure, Group Definitions and Correspondence Tables.

four concepts in Skill specialization as “i) the field of knowledge required, ii) the tools and machinery used, iii) the materials worked on or with, and iv) the kinds of goods and services produced.” The relationship of nine[7] major groups and four skill levels is summarized in Table 4.2. Actually, Table 4.2 is drawn as a skill rank with respect to formal education and training requirements of the occupation (International Labour Office, 2012). According to International Labour Office (2012), “1” stands for primary level of education which is dubbed as unskilled labor; “2” corresponds to both lower and upper secondary level of education and post-secondary education but not tertiary which is called as semi-skilled labor; finally, skilled labor is composed of “3” and “4”, where “3” means first stage tertiary education with short and medium duration and “4” denotes first stage tertiary education with medium duration and also second stage tertiary education. However, there are some mismatches among education and occupation in reference to Table 4.2 in Turkey, check Table 5.2 and Table 5.6 in Section 5.

Table 4.2: Mapping of ISCO-08 Major Groups to Skill Levels

ISCO-08 Major Groups	**Skill Level**
Managers	3+4
Professionals	4
Technicians and Associate Professionals	3
Skilled Agricultural, Forestry and Fishery Workers	2
Craft and Related Trades Workers	2
Clerical Support Workers	2
Services and Sales Workers	2
Plant and Machine Operators and Assemblers	2
Elementary Occupations	1

Source: International Labour Office (2012: 14).

As a result, we can capture both high – low skill facet and white – blue collar distinction. “Managers”, “professionals” and “technicians and associated professionals” are regarded as High Skilled White Collar (HSWC) while “clerical support workers” and “services and sales workers” constitute the group of Low Skilled White Collar (LSWC). On the one hand,

[7] 0 - “Armed Forces Occupations” is not reported in HLFS.

High Skilled Blue Collar (HSBC) includes “skilled agricultural, forestry and fishery workers” and “craft and related trades workers”; on the other hand, Low Skilled Blue Collar (LSBC) has “plant and machine operators and assemblers” and “elementary occupations” categories. Besides, we can also further aggregate these four classes into “high skilled” and “low skilled” parts which ensue the removal of white – blue collar debate. In such a case, it is more convenient to judge the skills on their own merits. For instance, presuming “a sales person” from LSWC category (ISCO08: code 52) as an indicator for higher skills than “metal, machinery and related trade workers” from HSBC category (ISCO08: code 72) may pave the way for possible biases and provoke discussion about the degree of which has more skill. Instead, we choose a more straightforward way and skill dimension is preferred over collar dimension. Dumont (2006) discussed the usage of ISCO classification for skill identification by simple regression analysis for the EU countries. High skilled – low skilled, white collar – blue collar or HSWC-HSBC-LSWC-LSBC groupings are found that they have no advantage over each other. For this reason, high skill – low skill was chosen to measure skill in this dissertation.

High skill includes occupations that “involve the performance of complex technical and practical tasks that requires an extensive body of factual, technical and procedural knowledge in a specialized field… *and* requires a high level of literacy and numeracy and well-developed interpersonal communication skills”; alongside of “complex problem-solving, decision-making and creativity based on an extensive body of theoretical and factual knowledge in a specialized field… *and* require extended levels of literacy and numeracy, sometimes at a very high level, and excellent interpersonal communication skills” (International Labour Office, 2012: 13). *Low skill*, in other respects, covers occupations that “involve the performance of simple and routine physical or manual task… *and* require physical strength and/or endurance… basic skills in literacy and numeracy” and also “performance of tasks such as operating machinery and electronic equipment; driving vehicles; maintenance and repair of electrical and mechanical equipment; and manipulation, ordering and storage of information… *and* require relatively advanced literacy and numeracy skills and good interpersonal communication skills” (International Labour Office, 2012: 13).

The challenging part is to identify relevant proxies for technology. Different manufacturing industries might have different capital-labor ratios and technology levels, which, in turn, can cause different responses to technology investments, institutional or organizational changes. To exemplify, if we consider NACE16 (manufacture of wood and of products of wood and cork, except furniture etc.) equal to NACE21 (manufacture of basic pharmaceutical products and pharmaceutical preparations) in terms of technology level and continue to work on the nexus of SBTC and wage inequality under the assumption of this, we may overlook some dynamics behind the wage inequality. To handle that restrictive framework, manufacturing sectors are split into four main technology intensity levels following Eurostat definition: low technology (NACE 10-18 and 31-32), medium low technology (NACE 19, 22-25, and 33), medium high technology (NACE 20, 27-30) and high technology (NACE 21 and 26) as seen in Table 4.3. Detailed matches of sectors and NACE codes can be found in Table A2. Moreover, in the light of Table A3, which tabulates the number of observations for four technology levels and two skill levels, it is possible to aggregate four technology groups into two main groups as low technology and high technology to get around the low number of observations in the high technology.

Therefore, manufacture of pharmaceutical products and pharmaceutical preparations, manufacture of computer, electronics and optical products, manufacture of chemicals, and chemical products, manufacture of electrical equipment, manufacture of machinery and equipment, manufacture of motor vehicles, trailers and semi-trailers and manufacture of other transport equipment compose *high technology*. On the other hand, *low technology* consists of manufacture of rubber and plastics products, manufacture of other non-metallic mineral products, manufacture of basic metals, manufacture of fabricated metals products except machinery and equipment, repair and installation of machinery and equipment, manufacture of food products, beverages, tobacco products, textile, wearing apparel, leather and related products, wood and products of wood, paper and paper products, printing a reproduction of recorded media, manufacture of furniture and other manufacturing.

Table 4.3: Aggregation of Manufacturing with respect to Technology Level

Manufacturing Industries	NACE Rev. 2 Codes 2-digit level	Aggregations of Manufacturing based on NACE Rev. 2
High-Technology	21	Manufacture of basic pharmaceutical products and pharmaceutical preparations;
	26	Manufacture of computer, electronic and optical products
Medium High-Technology	20	Manufacture of chemicals and chemicals products;
	27 to 30	Manufacture of electrical equipment; Manufacture of Machinery and equipment n.e.c.; Manufacture of motor vehicles, trailers and semi-trailers; Manufacture of other transport equipment
Medium Low-Technology	19	Manufacture of coke and refined petroleum products;
	22 to 25	Manufacture of rubber and plastic products; Manufacture of other non-metallic mineral products; Manufacture of basic metals; Manufacture of fabricated metals products, excepts machinery and equipment;
	33	Repair and installation of machinery and equipment
Low-Technology	10 to 18	Manufacture of food products, beverages, tobacco products, textile, wearing apparel, leather and related products, wood and products of wood, paper and paper products, printing and reproduction of recorded media;
	31 to 32	Manufacture of furniture; other manufacturing

Source: Eurostat.

4.3. INEQUALITY MEASURES

The remainder of Section 4 is planned to identify how to account for inequality. There are various measures of inequality such as relative mean deviation, coefficient of variation, standard deviation, Gini coefficient, decile dispersion ratio of different percentiles or measures of Mehran, Piesch, Kakwani, or Theil entropy. Throughout our analyses, decile dispersion ratio, put it differently - relative wage dispersion, is the mainstay of the wage inequality, as well as kernel density estimation which is utilized to demonstrate changes in wage distributions, but Theil entropy index is also used to support results obtained from wage dispersions. Division of a specific wage percentile to another point on the same wage distribution gives us a simple but most widely used wage inequality measure. Besides, this method enables us to uncover what happens along the wage distribution and how different tails respond to technology shocks rather than a single index value reflecting the entire wage inequality.

The (logarithm of) real hourly wage at 90^{th} percentile to 10^{th} percentile is commonly held as *overall wage inequality*, which means the ratio of the richest decile to the poorest decile. If the distance gets longer (shorter), wage inequality worsens (alleviates). However, it should be kept in mind that the overall measure does not have the power to clarify what is going on in the middle of the distribution or at the top and the bottom deciles. For the first problem, we construct upper tail and lower tail inequality measures to capture the information about the middle of the income distribution. For the second problem, the richest percentile (99^{th}) to the poorest percentile (1%) dispersion is generated.[8] The logarithm of real hourly wage at 90^{th} percentile to the median is the *upper tail wage inequality* while median to 10^{th} percentile is the *lower tail wage inequality*. To gain some insight into how the wage inequality changes in case of a technology shock, overall, upper-tail and lower-tail wage inequality measures are selected due to their simple but illustrative nature which makes them applicable directly to new counterfactual wage distributions.

[8] 99th to 1st percentile is only used for counterfactual analyses and not reported for descriptive statistics in Section 5.

Besides, in order to take a snapshot of the existing situations in Section 5, a generalized entropy class index is constructed to estimate within and between group inequalities separately. The general formula is as the following equation:

$$GE(a) = \frac{1}{a(a-1)}\left[\frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i}{\bar{y}}\right)^{a} - 1\right] \qquad [4.1]$$

where *a* is the income sensitivity parameter representing the weight given to distances between incomes at different parts of the wage distribution. Parameter *a* can be any real value. The value of GE (generalized entropy) is between zero and infinity. The former value represents an equal distribution whereas higher values represent higher levels of inequality. Lower values of *a* make the GE more sensitive to changes in the lower tail of the distribution whereas higher values of a make GE more sensitive to changes in the upper tail (Atkinson and Bourguignon, 2015). *a* is generally take values of 0, 1, and 2. For example, GE(0) is the mean logarithmic deviation while GE(1) equals to Theil Index and Equation [4.1] turns into the following the Equation [4.2], enabling us to estimate within and between inequality measures. The first term represents the within-group inequality and the second term represents the between-group inequality.

$$T = \sum_j \left(\frac{Y_j}{Y}\right) T_j + \sum_j \left(\frac{Y_j}{Y}\right) \ln\left[\frac{Y_j / Y}{N_j / N}\right] \qquad [4.2]$$

5. PRIMARY ANALYSES

This section essentially focuses on some descriptive statistics about the Turkish manufacturing sector in terms of technology and skill structures. After a brief introduction of employment structure, the second subsection includes wage distributions using kernel densities and also efforts to discover wage inequality at different parts of the wage distribution. To shed more light on the components of skill and technology, Theil indexes are constructed for more fragmented parts. By doing so, we lose information about behaviors of wage distributions in skill and technology terms but the sensitivity of general tendencies in wage inequality due to measurement selection can be checked in comparison with previous results.

5.1. EMPLOYMENT CHARACTER OF TURKISH MANUFACTURING SECTOR

Before scrutinizing wage inequality, nevertheless, we first want to depicture the employment character of the Turkish manufacturing industry with respect to some diffractions such as education, skill, and technology level. The structure of labor in the manufacturing sector is very substantial to understand the dynamics behind the wage inequality. Since the HLFSs have different sample sizes for each year, a table for employment with respect to skill level is constructed according to employment shares for four technology categories within two skill levels, see Table 5.1. It is possible to say, the Turkish manufacturing sector is characterized by low and medium low technologies. High technology can absorb only a tiny fraction of employment. On the other hand, to comprehend the economic magnitude of high technology, employment share is not sufficient and value added created at this part of the manufacturing sector should be incorporated into the scheme which is, in fact, out of the inequality scope we have dealt with. For the medium level technologies, the gap between medium low and medium high gets larger. The number of observations can be found in Appendix Table A4. The evolution of employment shares is rather consistent across years and additionally, high skilled and low skilled parts capture nearly equal shares in their technology groups.

Despite all, Table 5.1 provides some useful information about trajectories of technology and skill dimensions. Although the numbers in 2008 slightly deviated from the previous shifts in terms of change in magnitudes, the 2008 global financial crisis was not directly reflected in employment shares and we do not expect to see a significant crisis effect as we work on employment share which may only indicate technology shift. The only notable change was in 2009 when there was a relative loss of weight in medium high technology and we need more evidence to assert the reason for that decline. Besides, technology shift cannot be attributed to the 2008 crisis according to the data analyzed here. On the other hand, as pointed out in Doğruel (2020), Turkey has not shifted from its long run trend in the manufacturing sector.

Although the bulk of employment share is grabbed by low technology group, the fraction of high skilled employment lost nearly 4% from 2004 to 2015 while the fraction of low skilled employment maintained its level. 2006 was the year when low skilled surpassed in low technology manufacturing industry and since then high skilled had never managed to catch. The reverse image could be seen in medium level technology groups: high skilled captured greater share. However, medium low technology experienced this after 2012.

Medium low technology became an absorption mechanism, because the decrease in employment shares of other technology groups became of increase in medium low technology. Peak rise in high skilled employment share was more than 5% in 2012 and with 2012 the battle between high skilled and low skilled was over in favor of high skilled, from 2% behind to 1% ahead. Such a consistent path occurred only for the low skilled employment shares in the medium high technology and it was the third largest job creator. With 2% shrinkage in low skilled workers was the greatest decrease among other low skilled counterparts. Despite an important decrease of high skilled employment share in 2009, on overall, this decline was compensated in following years, resulting in no significant change over the period. On the other side, low skilled employment share experienced a similar fall in 2009 which had not recovered. The gap between high skilled and low skilled employment shares widened at the greatest proportions among other technology groups. At the end, medium level technologies became more skill biased.

High technology as expected possessed the minority of employment shares over the period, exhibited some rise and fall but could not exceed the 2005 level of 1.61% aggregately. In spite of changes in employment shares were not considerable compared to other technology levels, high skilled ratio had a decline to 0.54% in 2008 but exceeded 0.80% in the next years; whereas low skill ratio, on the other side, had a decreasing trend after 2009 which was interrupted in 2015. High skilled share was greater than low skilled on average, there were only three years LS ratio surpassed HS.

Table 5.1: Employment Shares w.r.t. Skills (%)

	LT		MLT		MHT		HT	
year	**HS**	**LS**	**HS**	**LS**	**HS**	**LS**	**HS**	**LS**
2004	28.14	26.41	10.48	12.67	10.55	10.25	0.75	0.75
2005	26.74	26.01	11.42	12.91	10.79	10.52	0.81	0.80
2006	26.08	27.47	10.82	13.49	10.61	10.01	0.67	0.86
2007	25.55	26.36	11.45	14.99	10.62	9.57	0.74	0.72
2008	23.49	24.93	11.99	16.14	11.65	10.55	0.54	0.70
2009	24.93	27.55	12.87	15.84	8.79	8.62	0.65	0.74
2010	25.44	27.71	13.72	13.62	9.38	8.62	0.77	0.74
2011	25.87	27.10	13.26	13.73	9.35	9.33	0.76	0.60
2012	25.62	25.91	15.53	12.36	11.71	7.53	0.81	0.54
2013	24.91	26.09	15.18	13.35	10.77	8.28	0.84	0.58
2014	24.85	26.89	15.16	13.40	10.95	7.43	0.78	0.54
2015	24.20	26.33	14.94	13.80	11.03	8.23	0.79	0.68

Source: Author’s own calculations.

The most striking results belong to Table 5.2. Diversification of employment shares according to education levels under the main headings of high – low skills. It is actually fair enough to talk about that when we mention high skills, those are not necessarily learned in school at least in as much as our conducted methodology. Education has a role to facilitate adaptation in the face of neutral technology shock e.g. general purpose technology. In other respects, skill term, in a broad sense, includes not only education and innate abilities but also on-the-job-training, learning-by-doing, familiarity with the tasks aroused from tenure, etc. For this reason, we can speak of some “informal” skills that are obtained through formal ways.

Therefore, skill is not necessarily learned in school is reflected at Table 5.2, where at the beginning of the period, the education level of half of the total employment in the manufacturing industry was below the primary school and at the end of the period, 1/3 of the total employment was barely absorbed by below primary school graduates.

Moreover, the primary school was the second largest group. Both below the primary school and the primary school consisted of 2/3 of all manufacturing employment. For both skill levels, there was a transformation from below the primary school to the primary school during those twelve years, possibly seeing the effects of compulsory 8-year education had enacted in 1997. That educational reform[9] has also led to higher returns to education in Turkey, particularly for tertiary education (Patrinos, Psacharopoulos, and Tansel, 2019). A similar cycle was also observed from the regular high school to the vocational high school. Share of college or more graduation increased to 8.43% and 3.32% in high skill and low skill categories respectively and those rises were the largest proportionately. But in high skill group, the college could surpass the high school, being the fourth largest education category, and approached to the vocational high school by 1.5%. The regular high school appeared to be less skilled than the vocational counterparts for all years. In addition to this, in the manufacturing sector, the vocational high school strengthened its position with respect to the regular high school. All in all, although there was a shift towards higher education, a quarter of total employment had still lower than the primary school education in 2015.

[9] 12-year compulsory education reform is not taken into account as it was enacted in 2012.

Table 5.2: Employment Shares w.r.t. Education (%)

	High Skill					Low Skill				
year	**below-PS**	**PS**	**HSC**	**VHS**	**COL**	**below-PS**	**PS**	**HSC**	**VHS**	**COL**
2004	25.38	8.36	4.92	7.43	3.83	26.85	8.63	6.23	7.06	1.23
2005	24.01	9.03	4.46	8.05	4.21	25.78	8.92	5.56	8.16	1.58
2006	22.69	8.70	3.92	8.49	4.37	24.47	9.97	5.11	8.63	1.82
2007	21.96	9.39	3.91	8.19	4.92	24.08	9.75	5.35	8.92	1.90
2008	20.38	9.37	3.69	8.80	5.43	23.29	10.04	5.62	9.03	2.02
2009	19.83	9.71	3.56	8.38	5.77	23.22	9.79	5.70	9.02	2.27
2010	20.26	11.15	3.71	8.03	6.16	22.88	10.98	5.21	8.53	2.40
2011	19.22	11.46	3.65	8.16	6.75	21.25	11.93	5.35	8.97	2.49
2012	20.00	11.80	3.98	10.46	7.42	20.99	12.48	5.38	8.48	2.67
2013	18.49	11.94	3.84	9.52	7.91	20.18	12.58	5.62	8.54	3.08
2014	17.53	12.86	3.93	9.66	7.75	19.72	13.48	5.45	8.40	2.96
2015	16.13	12.60	3.81	9.98	8.43	19.72	13.42	5.21	8.32	3.32

Source: Author’s own calculations.

5.2. WAGE DISTRIBUTIONS AND TAIL INEQUALITIES FOR AGGREAGATE GROUPS

This subsection sketches wage distributions and tail wage inequality figures using the top and the bottom deciles with the median wage and also starting with the aggregate case to more elaborated subgroups to put down to the fact of the current state. Graph 5.1 shows the wage distribution for the entire male sample. Two inferences are apparent: first, the wage distribution shifted to the right as its height got higher, but it is difficult to tell a significant change in its dispersion; secondly, the shape of distribution drastically changed in 2015, a small hump started to occur in the upper tail of the wage distribution, possibly a concept of related to polarization.

Graph 5.1: Wage Distribution: All Sample

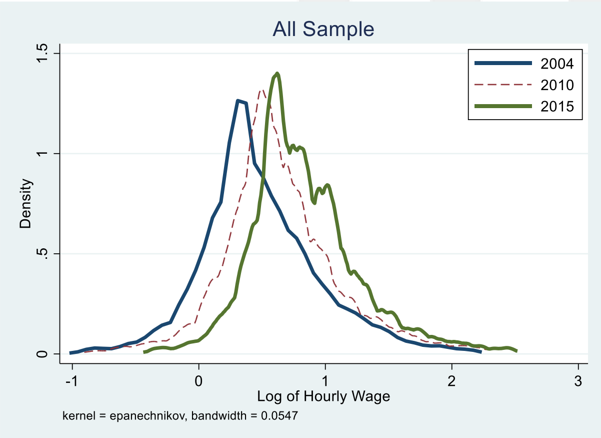


Figure 5.1: Wage Inequality: Percentile Ratio

Source: Author’s own calculations.

Detailed inspection of the upper and lower tail inequalities is shown in Figure 5.1. It is possible to say that overall male wage inequality recovered seriously since 2004 and its pace after 2011 accelerated. Besides, upper tail wage inequality almost remained the same until 2011 while started to decrease after 2011. At the lower tail of the wage distribution, the picture was not so clear. From 2006 to 2010, nearly there was no notable movement and the alleviation of the last years was not long lasting, going back to 2011 level in the year 2015.

When we look at the cumulative changes in wages from Figure 5.2, the vision of the evolution was more sightful. Previously we had seen that the common trend in all inequalities was downward but the relationship between upper and lower tail inequalities was quite blurred. By means of cumulative changes in wage, it is obvious that the divergence between the 10^{th} percentile and the 90^{th} percentile became larger in favor of lower tail in the process of time which also confirmed the decline in the male wage inequality in the Turkish manufacturing sector. Furthermore, the median wage increased faster than upper tail. So, not only lower tail inequality but also overall inequality declined. However, due to the base effect, convergence in tail wage inequalities remained relatively limited. Lower the wages, higher the increase in wages is another conclusion that can be deduced from. Figure 5.3, the variance of wage in natural logarithm, also reflected the downward trend in wage inequality in the broadest manner.

Figure 5.2: Cumulative Change in Wage

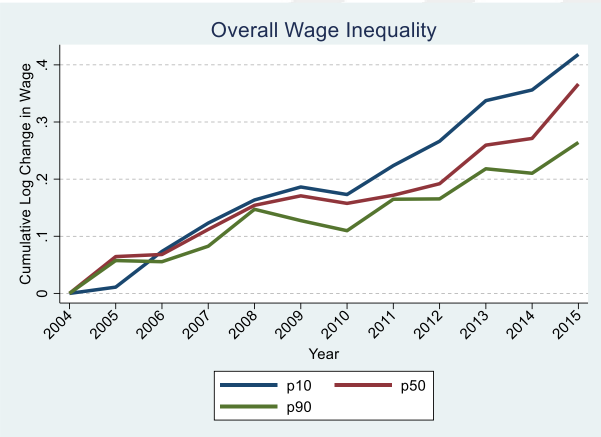
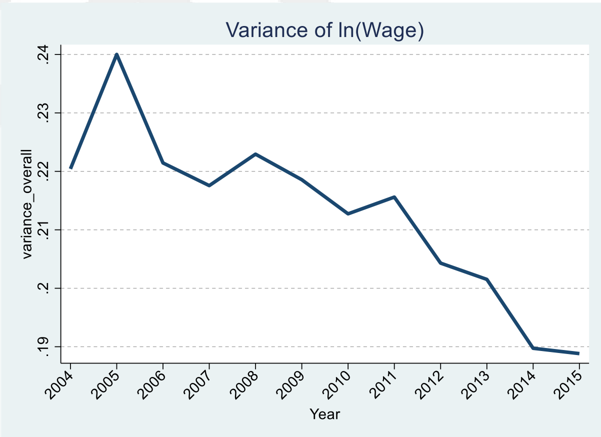


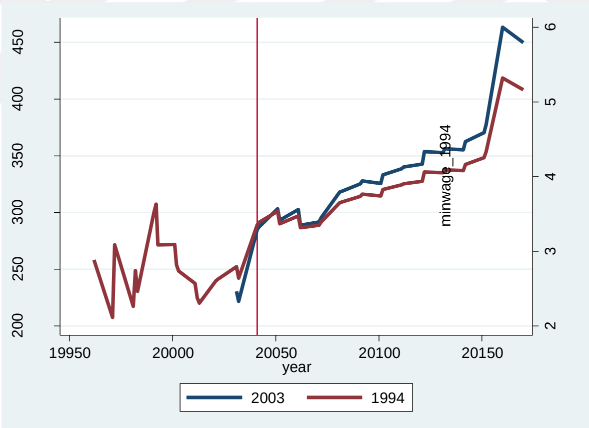
Figure 5.3: Variance of Log Wage



Source: Author’s own calculations.

As overall Turkish manufacturing sector witnessed lower wage inequality, such a change might stem from supply and demand factors of workers as well as labor market institutions. Changes in the individual attributes and unexplained part are other candidates for wage inequality. This unexplained part is also dubbed as residual which encapsulates skill biased technical change. However, we can investigate minimum wage whether it has a dramatic change during the considered period following the work of Bakış and Polat (2015). In Figure 5.4, monthly real minimum wages are given and the vertical line displays the year 2004, when the pay hike in minimum wage was greater than 40%. The blue line is deflated with respect to the 2003 base and the path of real minimum wage did not deviate much until 2016 when the nominal minimum wage increased from 1000 TL to 1300 TL. Therefore, period between 2004 and 2015 was not directly characterized by minimum wage increases. Figures 5.5 and 5.6 show how average wage and minimum wage went along with. Although there was no sharp deviation in trends of hourly minimum wage and hourly average wage, according to Figure 5.5, Figure 5.6 could provide more insight into their relative ratios. From 2004 to 2006, the minimum to average wage ratio increased considerably, then entered into a period of decline and rise until 2010 where 2008 was the bottom level after 2004. With the year 2010, the average wage began to lose its power consistently relative to the minimum wage.

Figure 5.4: Evolution of Real Minimum Wage



Source: Author’s own calculations.

Figure 5.5: Real Hourly Minimum Wage & Average Wage in the Manufacturing Sector

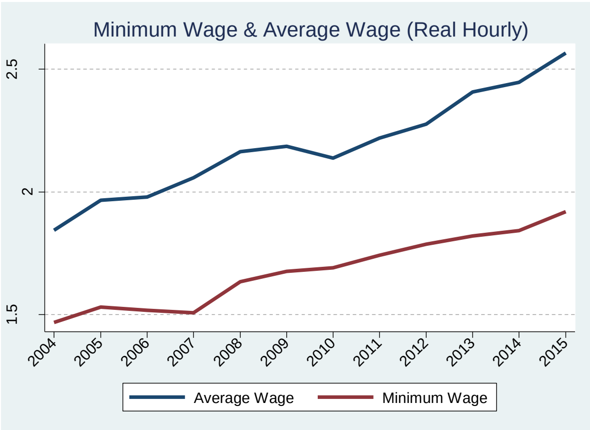
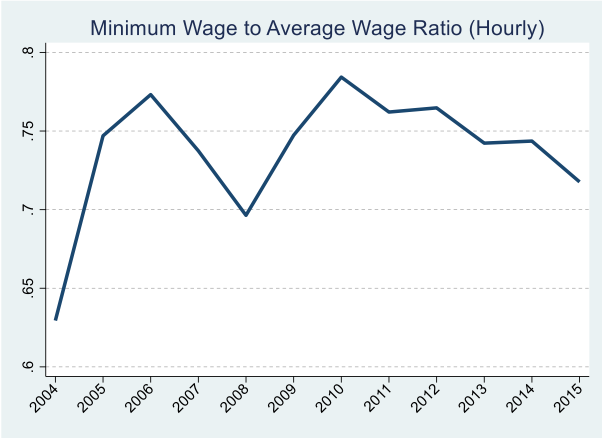


Figure 5.6: Minimum to Average Wage Ratio

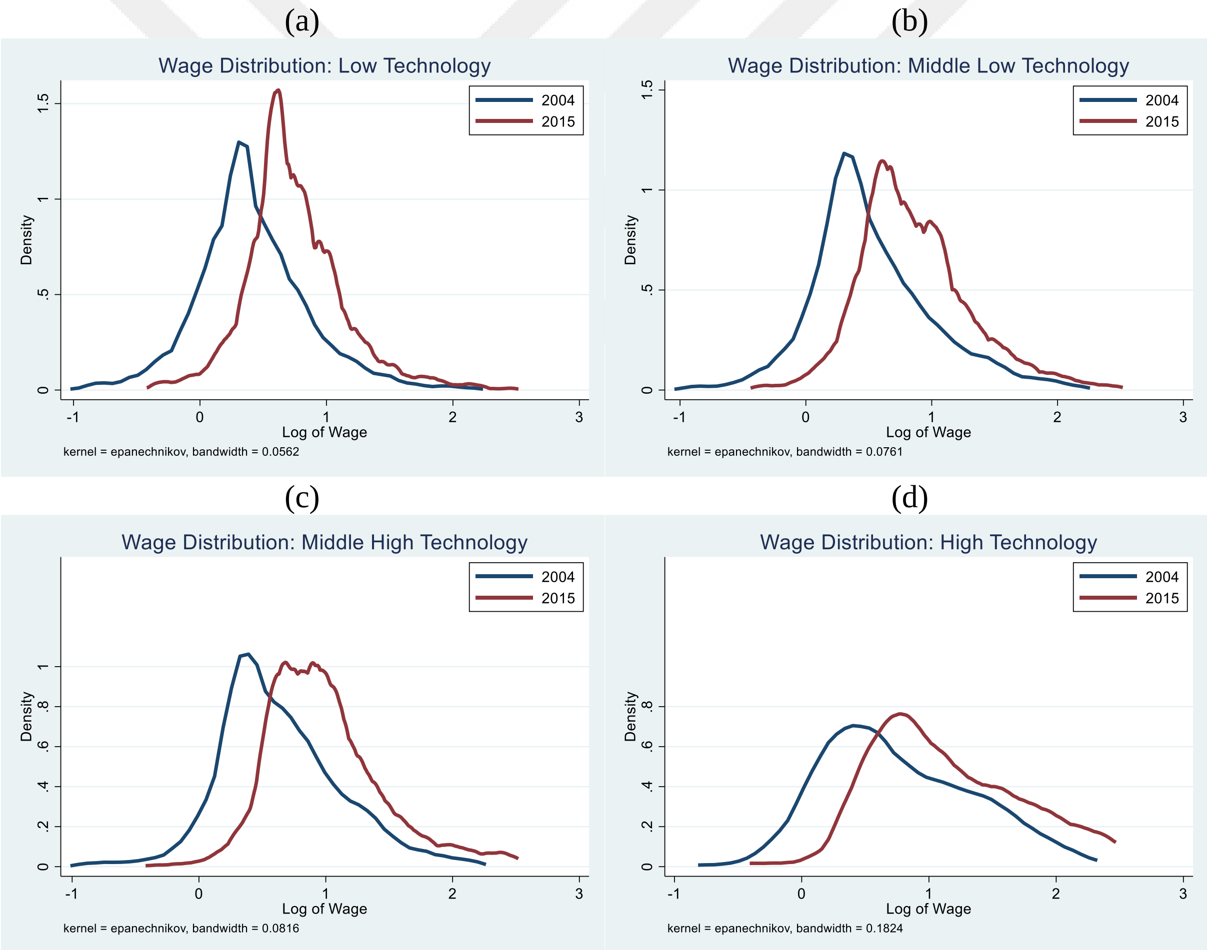


Source: Author's own calculations.

After an overview of wages at the aggregate terms, the very same rationale is applied for the more disaggregated terms. The first stage is to inquire about how wage distributions are shaped among four technology groups. All of the kernel densities, in the meanwhile, in this section are estimated for hourly real wage in natural logarithms. Graph 5.2, which is scaled at the same density level, depicts the evolution of wage distribution from 2004 to 2015. As we moved towards lower technology levels, wages became more equally distributed on account of shrinkage at the body of the distributions. In addition to that, as the technology level increased, tails of the wage distributions started to have different patterns. Lower tails were much stepper and the smoothness of upper tails vanished, especially at the low and medium low technology groups. Consolidation of wages at more than one area could reflect polarization in wages among high wage earners.

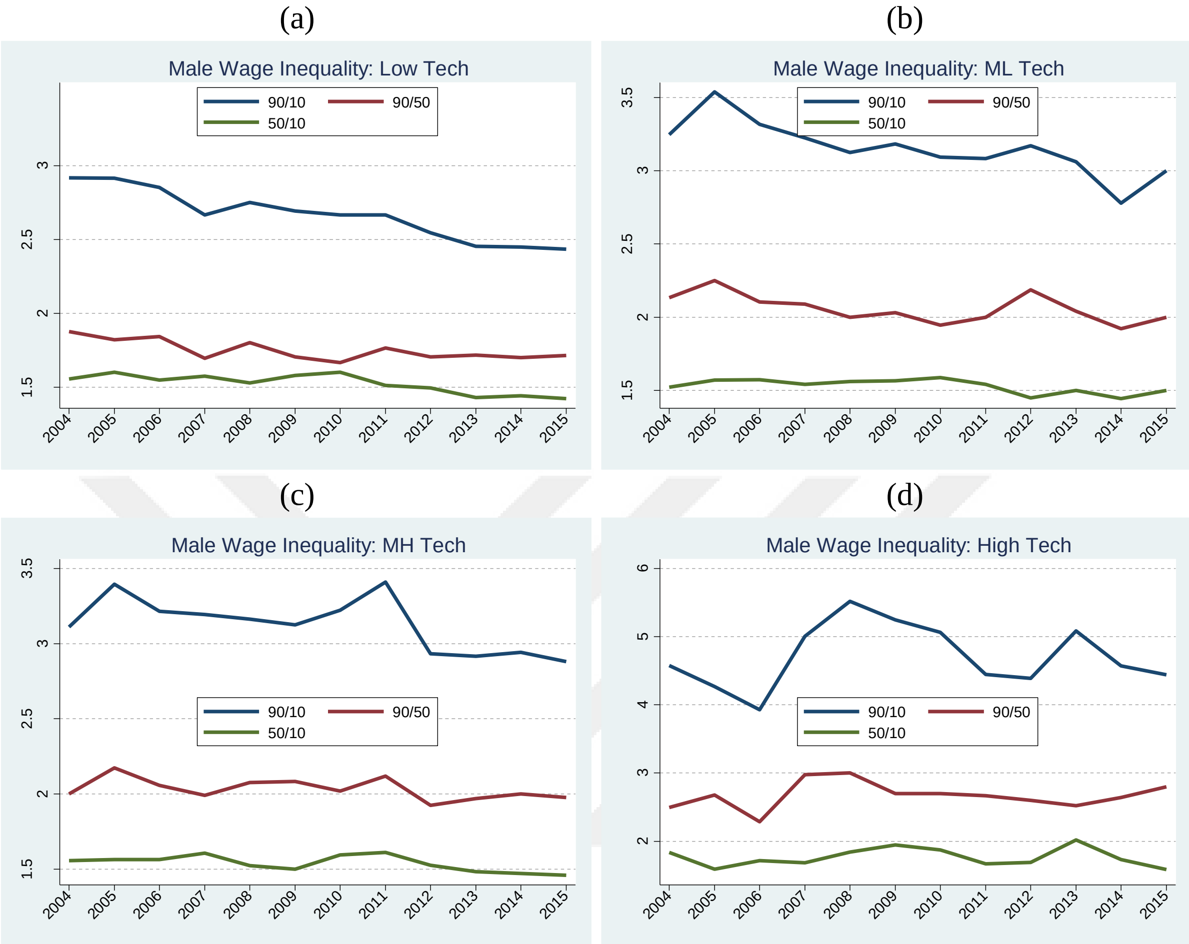
To account for wage inequality, we check overall, upper tail and lower tail wage inequalities in Figure 5.7. Except high technology, the vertical axis is constructed at the same scale to ease the comparison. More complicated technology directly meant more wage inequality. Furthermore, the upper tail had prominently higher wage inequalities than the lower tail counterparts. Lower tail wage dispersion was nearly equivalent to each other, moving around 1.5; besides, the contribution to the overall wage inequality by a majority emanated from the upper tail. In the same vein, again except for high technology, overall wage inequality had a downward trend; however, the volatile trajectory of high technology did not enable us to point out an exact trend. Table A5 in the appendix also confirms that wage inequality of all wage distributions greatly came out of variations in the 90th percentile. The 10th percentile was rather stable across all technology levels. For instance, in 2015, 10th percentile wage levels did not exceed 2 whereas wage levels ranged between 3 to 10 at the 90th percentile. Change in the upper tail inequality remained limited for the top two technology levels from 2004 to 2015. Consequently, the sophistication degree of industries was closely associated with high wage inequality in all measures.

Graph 5.2: Kernel Densities: Technology Level



Source: Author’s own calculations.

Figure 5.7: Wage Inequality w.r.t Technology Level: Percentile Ratios

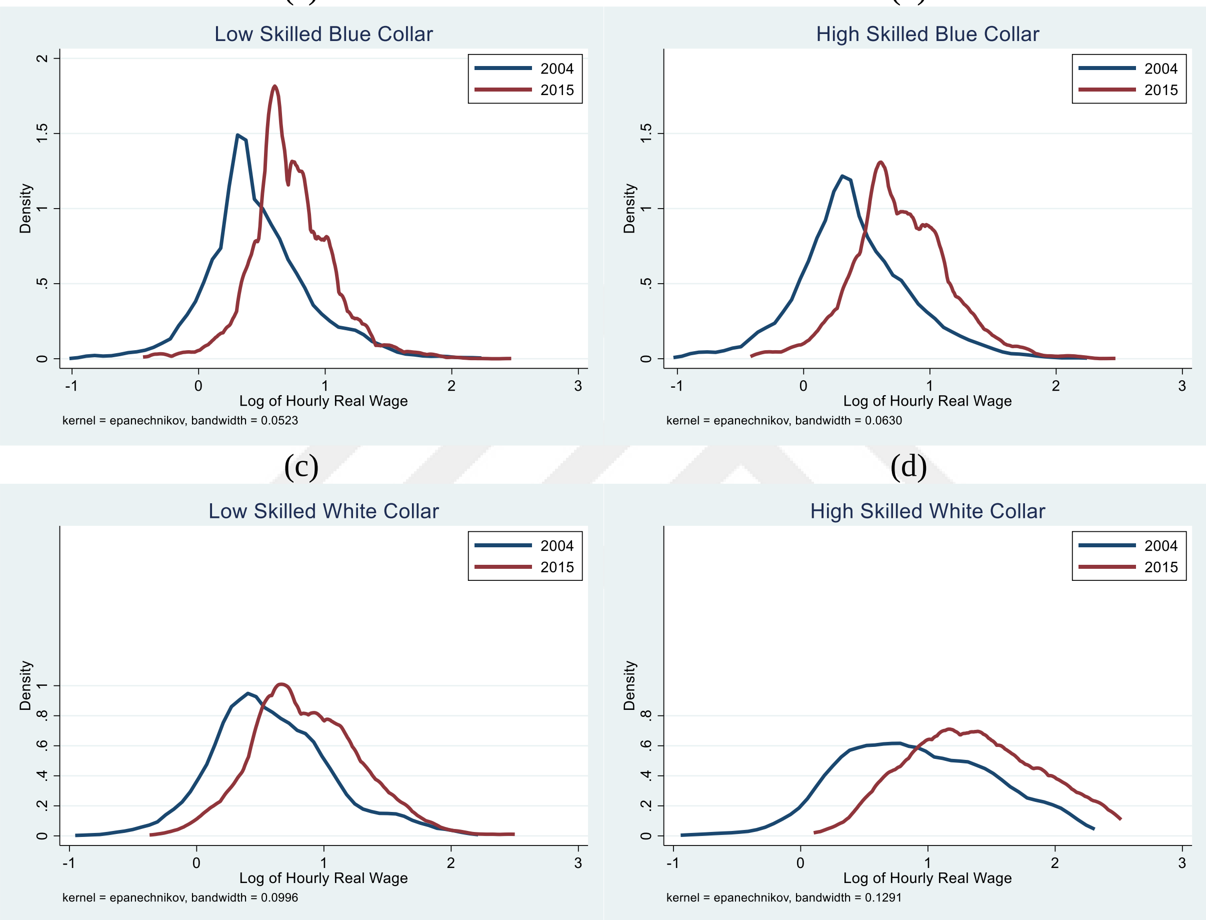


Source: Author's own calculations.

Subsequent to the introduction of wage distributions and inequalities at four technology groups, we pass on to the skill facet through the agency of ISCO taxonomy mentioned in Table 4.1. As a first step, four skill groups are analyzed as in the case of technology, then both skill and technology dimensions are reduced to two groups as low and high, to create an opportunity to check against the results of the following section. Graph 5.3 visualizes wage distributions for high – low skills and white – blue collars. LSBC and HSBC experienced similar trends but HSBC dispersion was greater than LSBC dispersion, depicting more unequal distribution in higher skill. Actually, in all figures, the height of distributions got taller so this could be traces of a decrease in within group inequality. As we move into a more skilled group, the relevant group suffered from inequality more than the former. There was a deformation in 2015 that should be emphasized on. At the upper tail of the wage distribution, except for HSWC, a second hill eventuated, indicating potential polarization, just in the case of the technology facet.

Graph 5.3: Kernel Densities: Skill Level

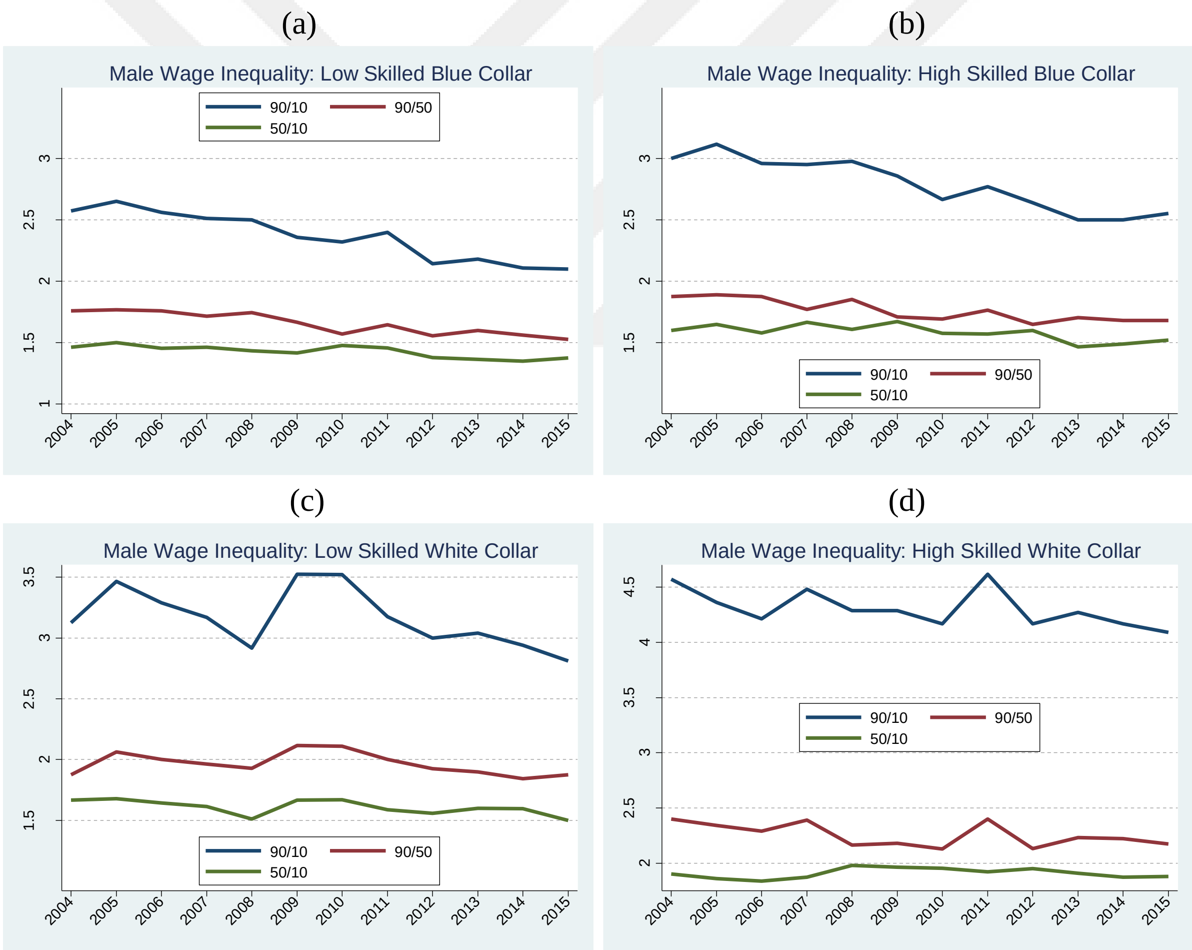
(a) (b)



Source: Author’s own calculations.

To account for between group inequalities, we need to refer to Figure 5.8 but we ended up with similar trends and tendencies as in Figure 5.7. Overall wage inequality decreased radically along the same line in all groups and the upper tail suffered from inequality more than the lower tail. As to whether there was a movement from low skilled to high skilled or blue collar to white collar in figures, we noticed a deterioration in wage inequality. Therefore, the choice of how the skill is defined in terms of high – low skill or white – blue collar is expected not to alter the main outcome of SBTC on wages. There are only two differences between skill and collar perspectives in Figure 5.8: first, 90/10 ratio is much volatile in white collar distinction while tail inequalities are closer to each other in blue collar distinction; second, at the skill dimension, when a worker belongs to high skill group, that worker's wage could deviate greatly than workers at the same skill level. Finally, we can say that as the skill level increased both between skill groups inequality and within group inequality scaled up as well.

Figure 5.8: Wage Inequality w.r.t Skill Level: Percentile Ratios

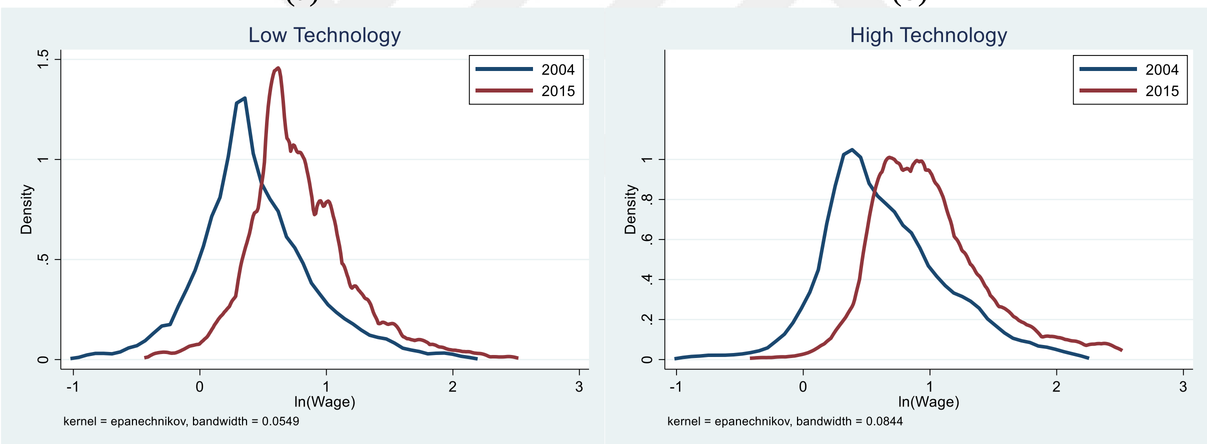


Source: Author's own calculations.

Thereafter, the same procedure is applied with regard to more aggregated technology and skill levels. Graph 5.4 and Figure 5.9 indicate results for low and high technology and kernel densities resemble to low and medium high technology, respectively since those are dominant technologies in their own categories. Changes in the shape of HT wage distribution remained more limited due to the low number of observations in high technology.[10] On the other hand, LT was suppressed downward converging to MLT wage distribution. When wage inequalities are examined into by Figure 5.9 to comprehend whether there is any difference from the disaggregated technology definition, results are in harmony with the previous definition, and the only difference springs from loss of deviation in the overall wage inequality although the common trends are preserved.

Graph 5.4: Kernel Densities: Aggregated Technology Level

(a) (b)

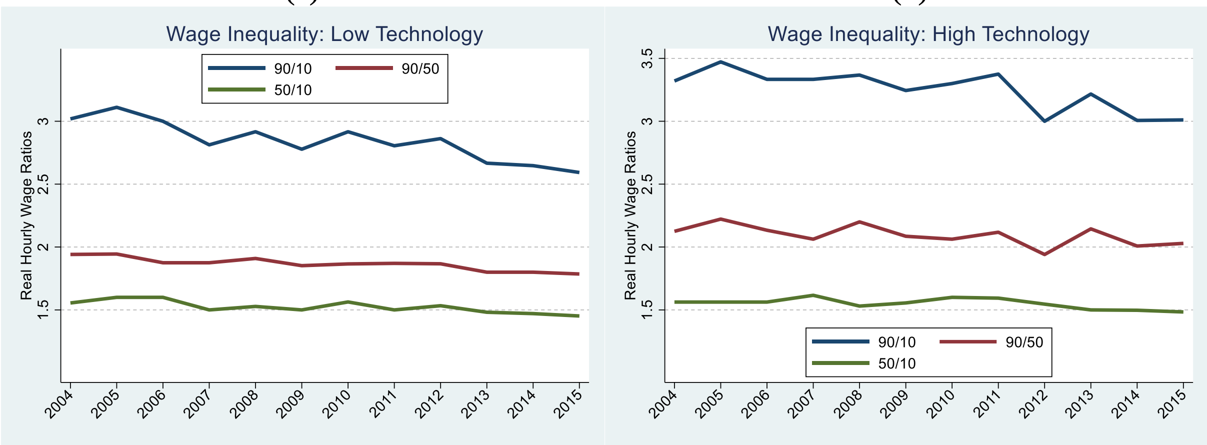


Source: Author's own calculations.

[10] Those aggregated high technology and low technology can create confusion with high-low technologies from four scaled counterparts. To cope with such a problem, from now on high-low technologies mean aggregated HT and LT unless otherwise stated.

Figure 5.9: Wage Inequality w.r.t Aggregated Technology Level: Percentile Ratios

(a) (b)



Source: Author's own calculations.

Identical graphs and figures are also drawn for high and low skill groups, see Graph 5.5 and Figure 5.10. Exactly same comments are valid for aggregated skill dimensions as well. Nevertheless, the wage inequality phenomenon turned out to be more severe in skill than technology partition and the backbone of this severity was directly associated with "low" parts. In other words, wages in low skill or low technology were stuck into a place where the movement area was more restricted than high counterparts. Workers who had low skill or work in a low technology manufacturing firm could not positively differentiate their wages, in particular when they were paid poorly. Because workers at the lower tail of wage distribution earn lower wages irrespective of their skill or sophistication degree of the technology they work in. Probably, the lower tail is characterized by some certain jobs; no matter what features they have, they are paid low wages.

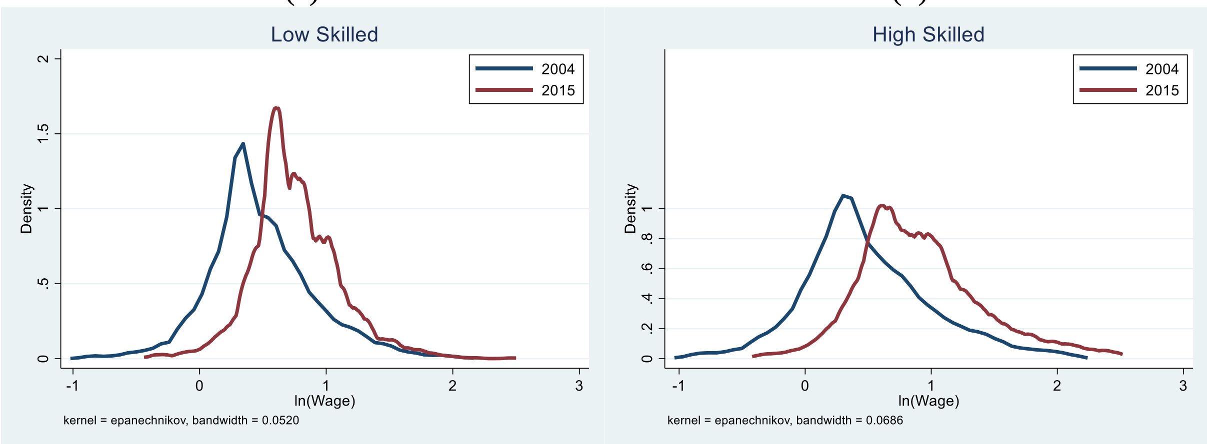
Table A5 supplies us with the necessary data to claim this argument. 10^{th} percentile real hourly wages are lower than 2 in 94 cases out of 96 and ranges from 0.89 to 2.04, while 90^{th} percentile real hourly wages are between 2.48 and 9.85. Employment in a higher technology manufacturing industry directly pays more but the gap between high skilled and low skilled increases dramatically as we climb up in technology ladder. If someone has low skill, which is defined in terms of occupation, the technology level of the industry he works in does not drastically differ from his wage rate. The 90^{th} percentile wage earner had real hourly wage of 2.95, 3.69, 3.69, and 3.93 in 2015 for LT, MLT, MHT, and HT, respectively; and in

2004, the same wages were 2.48, 3.1, 3.32, and 3.54. On the other hand, the 10^{th} percentile wages for low skills in 2015 were 1.48, 1.43, 1.64 and 1.57 for LT, MLT, MHT and HT, respectively; while in 2004 those wages were 0.98, 1.06, 1.16 and 1.06. The pattern asserting that higher technology generates higher wages was broken down when the skill facet had been incorporated into the scheme; in 2015, the 10^{th} percentile wage was higher in LT than MLT and in 2004, MHT paid more wage than HT in the 10^{th} percentile. However, such "inconveniences" were observed only at the lower tail. The *hierarchical wages* are the distinctive property of the upper tail, explicitly 90^{th} percentile.

90^{th} percentile real hourly wages of highly skilled in 2015, by contrast, were 4.06, 4.92, 5.91, and 9.85 for LT, MLT, MHT, and HT, respectively, while 2.84, 3.72, 3.97, and 6.14 in 2004. On the contrary, high skilled wages at the 10^{th} percentile in 2004 were 0.89, 0.96, 1.13, and 1.18 for LT, MLT, MHT, and HT, respectively; while, in 2015, they became 1.33, 1.48, 1.77, and 1.91. The hierarchical wages were held across all high skilled groups for all years, except 2008 when the 10^{th} percentile wage was 1.33 in MHT and 1.32 in HT. The mirror image of the same "inconvenience" at the lower tail, this time, could be seen between high – low skill. For all LT and first years of MLT and MHT, workers were punished due to their high skill levels. That is to say, low skilled workers who were located at the 10^{th} percentile of the wage distribution, earned more wages than the high skilled counterparts. That situation was reversed in 2010 for medium level technologies. What was peculiar to the lower tail was not experienced at the upper tail, and high skilled wages at the 90^{th} percentile were always considerably greater than low skilled. To be precise, it could be seen the extent of variation in wages not only across technologies but also across skills. When we dynamically examine the entire period, there was a wavelike movement in real wages; however, from 2004 to 2015, all subdivisions had a surge in real hourly wages in spite of violation of hierarchical wages. Finally, high skilled and low skilled distinction, as a matter of fact, was more obvious when we had split technology as high and low technology.

Graph 5.5: Kernel Densities: Aggregated Skill Level

(a) (b)



Source: Author's own calculations.

Figure 5.10: Wage Inequality w.r.t Aggregated Skill Level: Percentile Ratios

(a) (b)

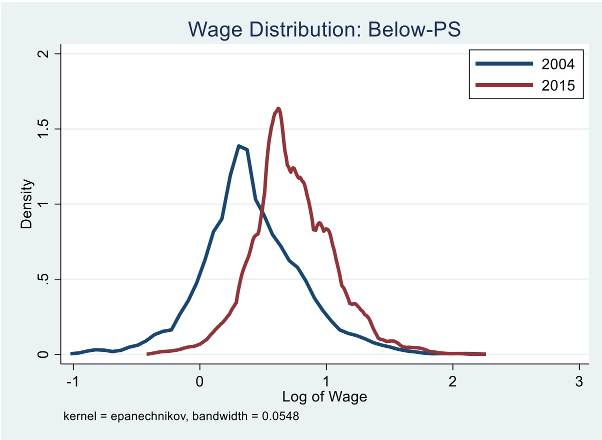
Source: Author's own calculations.

The last perspective we want to add to the framework built above is education, which is the most prominent variable among the HLFS that can be regarded as a proxy for skill. Notwithstanding the general perception of education as an indicator of skill, ILO classification to skill specification is used in section 6 due to the structure of the Turkish manufacturing industry in which the ratios of PS and Below-PS collectively were approximately 69% and 54% in 2004 and 2015. Besides, we pay regard to the methodology of ILO classification discussed in Section 4.2. Education fundamentally determines both the collar type and skill level of occupations; and then we aggregate those occupations to construct skill levels. Graph 5.6 illustrates basic kernel densities at five education levels. There are three different patterns for education groups: first, below-PS and PS; second, HS and VHS; finally, COL. To account for inequality, Figure 5.11 is drawn which depicts overall as well as upper and lower tail wage inequality at the same scale, except the college degree.

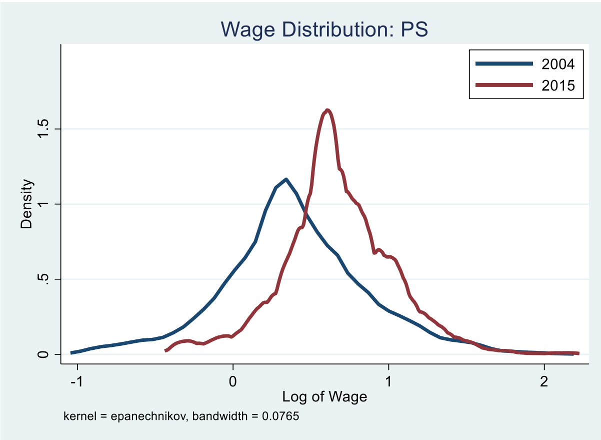
As we move towards higher education, between wage inequality increased but all inequalities scaled down substantially from 2004 to 2015, aside from college. The persistency of wage inequality within college graduates could be seen by all three wage inequality indicators, neither overall nor tail inequalities improved. High school and vocational high school had rather diversified paths than below primary school and primary school. The distance between upper and lower tail wage inequalities was negligible in below-PS and PS compared to other education levels; even between 2009 and 2011, the dominance of lower tail wage inequality over upper tail was observed for the first time. However, for high school and vocational high school, the upper tail ratio was always greater than the lower tail and only after 2011, they converged to each other. Additionally, the stable path of the lower tail still existed in educational groupings and the majority of recovery in overall wage inequality came from the decrease in upper tail inequality. Below primary school had the lowest wage inequality, nearly half of college case. Unlike the groups at the far ends in the educational distribution, within wage inequality reduced sharply.

Graph 5.6: Kernel Densities: Education Level

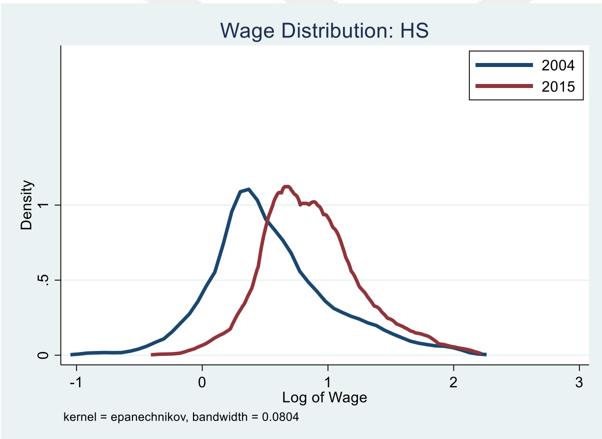
(a)



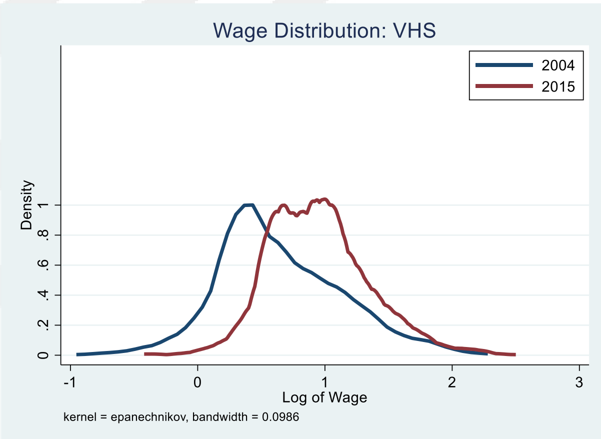
(b)



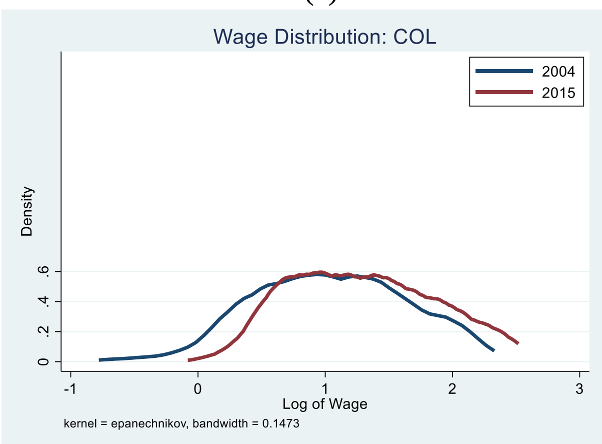
(c)



(d)

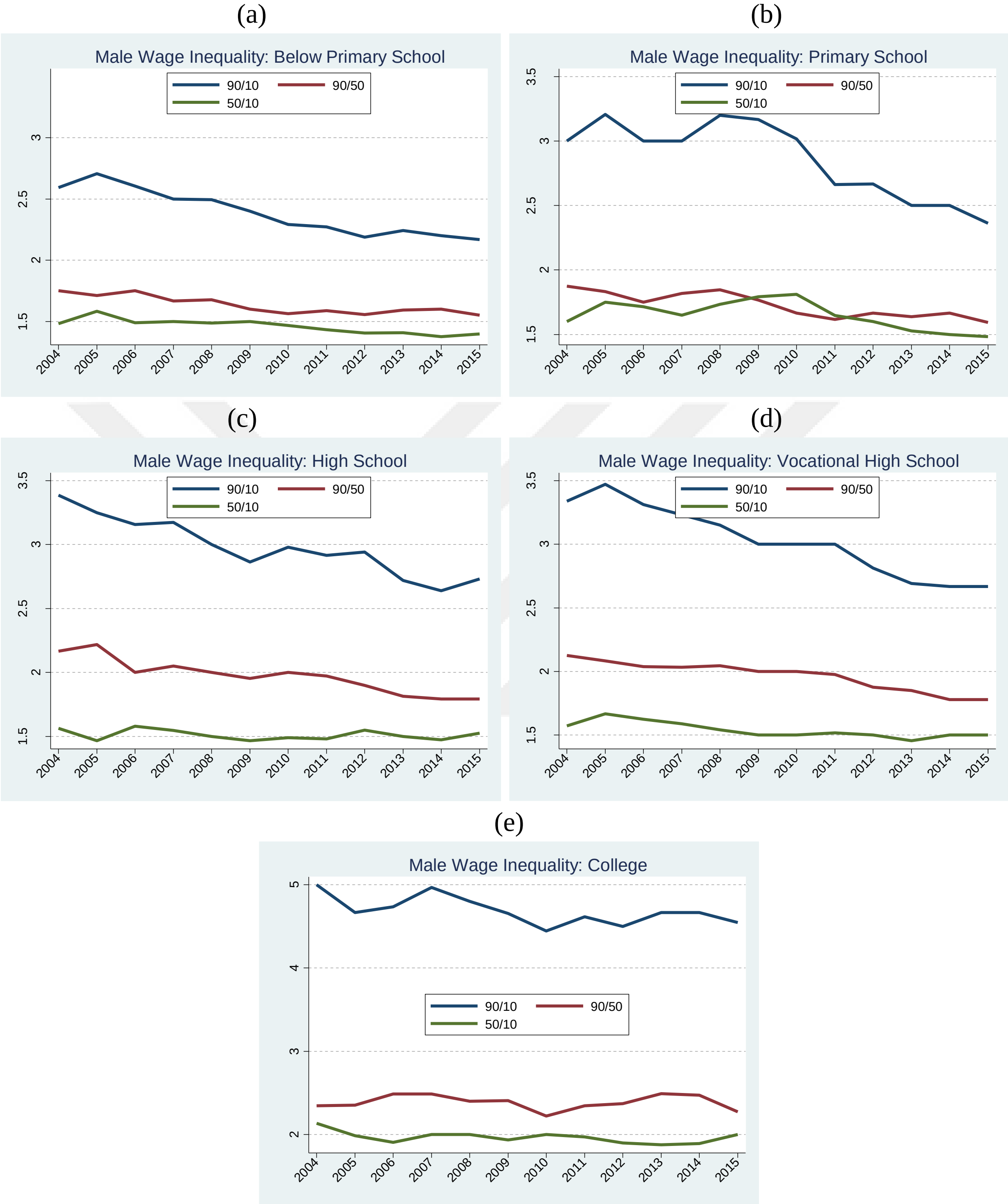


(e)



Source: Author’s own calculations.

Figure 5.11: Wage Inequality w.r.t Education: Percentile Ratios

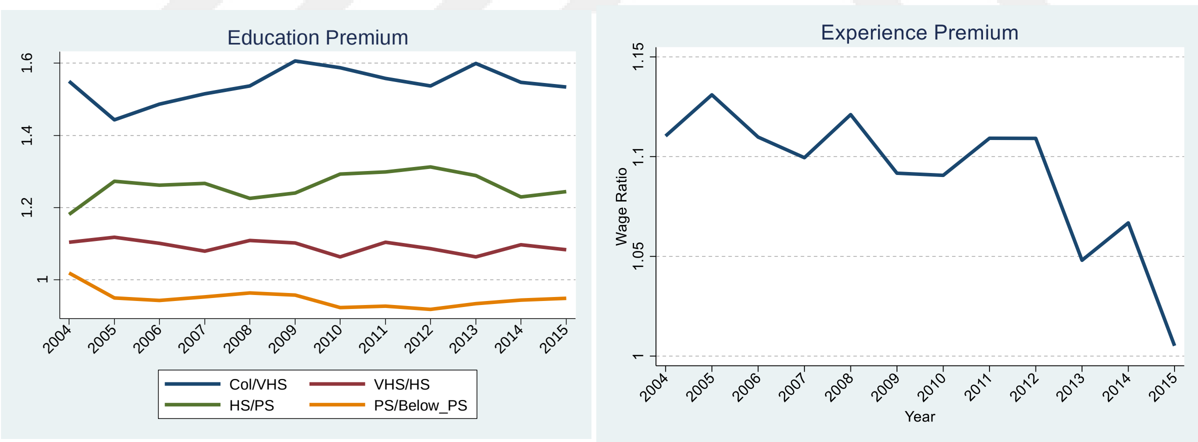


Source: Author's own calculations.

Finally, we lay stress upon education and experience premiums. Education premium is calculated by dividing wages of each two successive education groups as in Figure 5.12 (a), which contains supportive arguments for the aforementioned analyses. It is seen that below primary school had higher wages than primary school, violating the order of more education brings forth more wage. Nonetheless, higher education apart from PS, led to better paid jobs. Vocational high school graduates were paid %20 to %30 more than regular high school graduates and independent from the skill level of graduates, college degree collectively earned nearly %60 more than subsequent education group. The issue of experience is also another determinant of wage, so in Figure 5.12 (b), experience premium is obtained through the ratio of wages between 45 and 55 to wages between 25 to 35. On that account, experienced employees had more power to get higher wages but after 2012, experience has started to play a minor role, and even in 2015, the distinction almost faded away.

Figure 5.12: Education and Experience Premiums

(a) (b)



Source: Author’s own calculations.

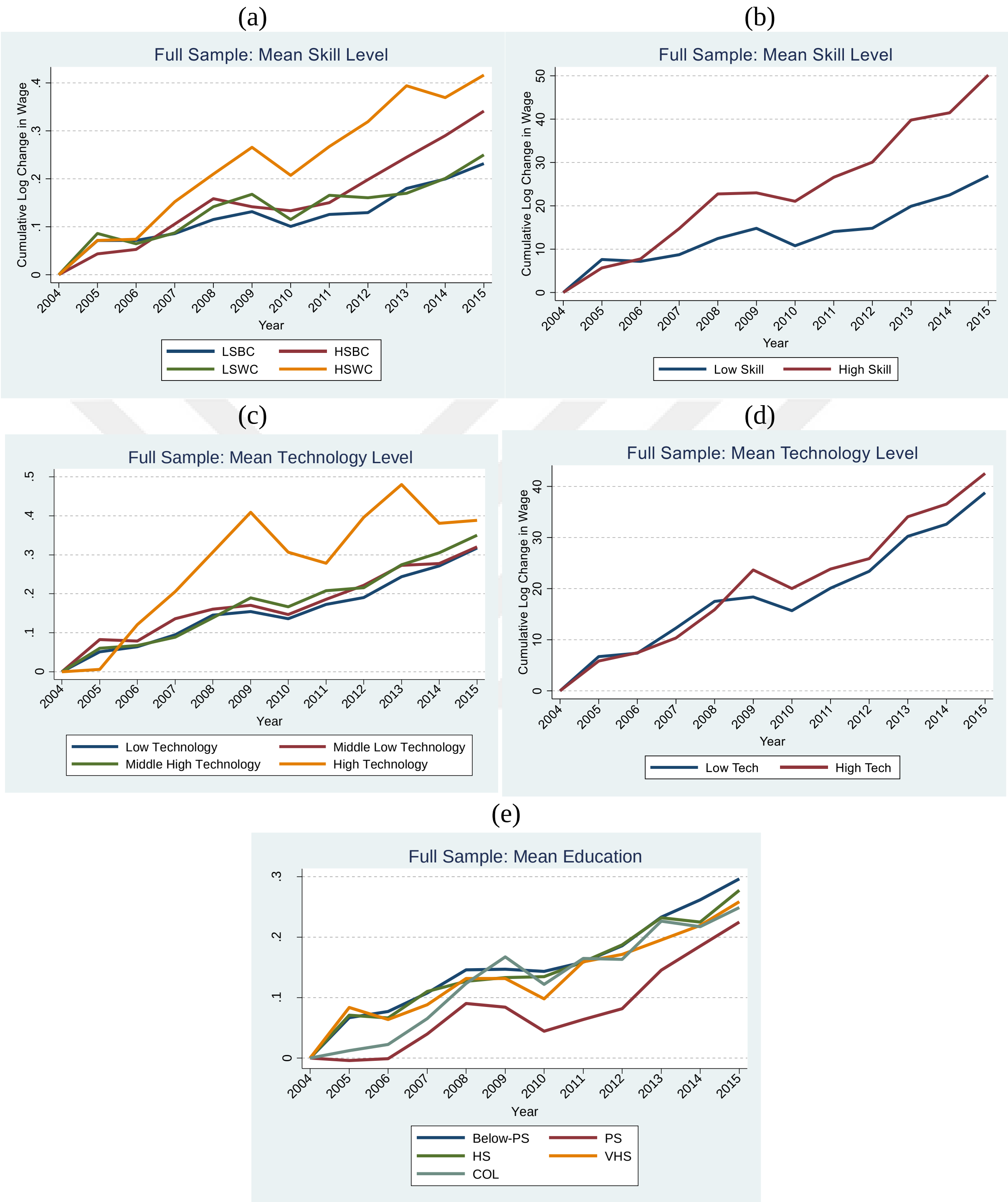
We try to demonstrate skill side using occupation and technology fractions as well as roughly education level. In a nutshell, general tendencies in wages are distilled out of all figures constructed in this section can be found in Figure 5.13. Cumulative changes are described with respect to white – blue collar in part (a), high – low skilled in part (b), four level technology grouping in part (c), and high – low technology in part (d). The last part is devoted to the cumulative change in wages according to educational level.

The cumulative increase in HSWC was almost higher than other collar groups except for the first two years. But, since then, HSWC significantly diverged from the rest and LSBC unsurprisingly performed the worst scenario. The brown line of HSBC was the second successor of HSWC after 2011. There was a battle between HSBC and LSWC until 2011; however, within the research period, we could assert that the war had been over in favor of HSBC. Thus, HS diverged from the LS independently of the collar. The relative improvement of LSWC over LSBC was ended in 2013 and two strands occurred in the figure: first, LSWC and LSBC moved together and drifted apart from the HS counterparts; and second, HSBC had an outstanding performance to catch HSWC. As a result, we could find another support for aggregation of occupation with respect to skill rather than collar, because the former followed a similar route. That is why characteristic grouping should be held on high – low skill ground and their diverging paths can be found in part (b) of Figure 5.13. Despite the amelioration of wages in favor of low skilled manufacturing workers until 2006, the continuous divergence characterized remaining years and wage inequality between skill levels got worse.

When we look at the same figure for technology level in the part (c), besides of high technology sectors, low and medium level technologies overlapped in many years whereas the only differentiation was rooted in low technology which was slightly lower than medium level technologies. On the other hand, from Table A3 in Appendix, where the number of observations listed, it can be seen that detailed refining is not eligible especially for high technology. Therefore, we merge high technology with medium high technology, and medium low technology with low technology and by doing so, we split the technology level in the manufacturing sector as high – low technologies. Relative improvement or at least stability of wage inequality in favor of low technology disappeared in 2008 and the technology separation entered into a new phase where high technology drifted away from low counterparts. Therefore, between technology groups wage inequality deteriorated after 2008.

Cumulative changes in wages according to educational categories had rather interwoven paths except for the primary school line. Wages in regular high school coincided with vocational high school wages throughout the period and college wage joined that path after having an acceleration in the speed of increase in wage in the second half of the 2010s. Results of cumulative change in wages listed in part (e) are in accord with Figure 5.9 for below-PS, PS, HSC, and VHS categories, but as the mean wage of COL increased considerably without having no significant recovery in overall and tail wage inequalities, it is possible to state that wage increase of COL spread over the entire wage distribution, so the existing inequalities were sustained in spite of acceleration in college wage.

Figure 5.13: Cumulative Changes in Wage Groups



Source: Author's own calculations.

5.3. EVOLUTION OF INEQUALITY INDEX

After a glance at the general picture of wage inequality, a need manifests itself to unfold inequality into more detailed parts and then gradually aggregate them again into the groups mentioned in Section 5.2 to compare results. In this subsection, all tables enumerate four main outcomes: GE(1) as Theil index, population share, income share and mean wage. Population share indicates the relative weight of wage earners in a specific group among the full manufacturing sample while income share stands for the income portion captured by a specific group among total wages paid in the manufacturing sector. Bold numbers correspond to a rise in that statistics, for this reason, bold numbers in GE(1) columns mean wage inequality in that group increased from 2004 to 2015. Furthermore, mean wage is not marked as bold due to the secular increasing structure.

To start with, Theil index results are given for 24 manufacturing industries in Table 5.3 and only 9 out of 24 industries experienced deterioration in wage inequality within themselves. Grey colored rows demonstrate high technology industries and 5 out of 7 high technology industries within wage inequality increased. Manufacture of Basic Pharmaceutical Products and Pharmaceutical Preparations and Manufacture of Electrical Equipment were only industries having lower wage inequality in 2015, but their total population share was barely 1.5% in the manufacturing sector. On the other hand, higher wage inequality in the low technology was observed in Manufacture of Wood and of Products of Wood and Cork, Manufacture of Paper and Paper Products, Manufacture of Coke and Refined Petroleum Products and Manufacture of other Non-Metallic Mineral Products, whereas inequality diminished in the rest 13 low technology industries. Although Manufacture of Wood and of Products of Wood and Cork was the most equally paid industry in 2004, lost its place to Manufacture of Leather and Related Products in 2015. Elementary Occupations was the most unequal industry in 2004. Manufacture of Computer, Electronic and Optical Products ascended one step further and became the most unequally paid industry in 2015. Manufacture of Wearing Apparel was the most labor creating industry in 2004 but lost 5% share and Manufacture of Food Products became the new industry that employed most worker in the manufacturing sector. Manufacture of Tobacco Products remained as the least worker employing industry.

Besides, income shares were always greater than population share in high technology while in low technology, both cases could be seen. Between and within Theil indexes also support our primary results. Moreover, between group wage inequality was much lower than within group inequality and the former increased while the latter decreased during our period.

Table 5.3: Evolution of Theil Index: Industry Level

		GE(1)		Pop. Share		Income Share		Mean Wage	
	Nace2	2004	2015	2004	2015	2004	2015	2004	2015
10	Food	0.1333	0.1110	0.1122	**0.1269**	0.0973	**0.1097**	1.5900	2.2186
11	Beverages	0.1485	0.1367	0.0077	0.0047	0.0097	0.0055	2.2852	3.0068
12	Tobacco	0.1069	0.1032	0.0016	0.0013	0.0028	**0.0030**	3.1209	6.0405
13	Textiles	0.1019	0.0736	0.1070	**0.1170**	0.1021	**0.1079**	1.7502	2.3667
14	Wearing Ap.	0.0996	0.0805	0.1472	0.0952	0.1356	0.0818	1.6890	2.2049
15	Leather	0.0982	0.0519	0.0345	0.0239	0.0304	0.0188	1.6157	2.0094
16	Wood	0.0709	**0.0985**	0.0336	0.0254	0.0259	0.0217	1.4153	2.1935
17	Paper	0.1408	**0.1518**	0.0141	**0.0172**	0.0161	**0.0197**	2.0906	2.9347
18	Printing, Media	0.1271	0.1202	0.0205	0.0151	0.0201	0.0158	1.8016	2.6821
19	Coke, Refined Pet.	0.1442	**0.1681**	0.0020	**0.0027**	0.0032	**0.0051**	2.9121	4.8540
20	Chemicals	0.1325	**0.1599**	0.0533	0.0221	0.0578	0.0276	1.9880	3.2080
21	Pharmaceutical	0.1613	0.1313	0.0054	**0.0054**	0.0083	0.0075	2.8266	3.5707
22	Rubber, Plastic	0.1681	0.0903	0.0475	0.0472	0.0496	0.0436	1.9121	2.3702
23	Nonmetallic Min.	0.1150	**0.1198**	0.0696	**0.0887**	0.0680	**0.0900**	1.7929	2.6011
24	Basic Metals	0.1430	0.1241	0.0461	**0.0637**	0.0565	**0.0766**	2.2488	3.0888
25	Fabricated Metal	0.1141	0.0831	0.0642	0.0670	0.0615	0.0607	1.7558	2.3259
26	Comp, Elct, Optics	0.1858	**0.2202**	0.0096	0.0093	0.0126	**0.0140**	2.4008	3.8807
27	Electrical Eq.	0.1243	0.1131	0.0312	**0.0388**	0.0355	**0.0425**	2.0837	2.8130
28	Machinery and Eq.	0.1197	**0.1267**	0.0431	**0.0568**	0.0463	**0.0634**	1.9706	2.8647
29	Motor Vehicles	0.1230	**0.1352**	0.0721	0.0658	0.0911	0.0820	2.3176	3.1966
30	Other Transport	0.1068	**0.1184**	0.0082	**0.0091**	0.0095	**0.0119**	2.1373	3.3544
31	Furniture	0.0754	0.0738	0.0532	**0.0656**	0.0434	**0.0576**	1.4926	2.2527
32	Other Manufac.	0.1155	0.1124	0.0144	0.0131	0.0146	0.0126	1.8592	2.4616
33	Repair and Install.	0.2074	0.1712	0.0018	**0.0181**	0.0021	**0.0211**	2.1766	2.9802
	Theil (between)	0.0101	**0.0127**						
	Theil (within)	0.1189	0.1090						

Source: Author’s own calculations.

According to Table 5.4, the picture got strengthened when industries were aggregated into four technology levels and across technology groups, wage inequality increased slightly from 0.0058 to 0.0072 despite a decrease in within technology groups. However, between group inequality almost disappeared when we aggregate 24 industries into 4 technology levels. Although, in 2004, medium level technologies violated the order, higher technology caused to greater Theil index, and for high and medium high technologies, wage inequality further rose, while medium low and low technologies experienced a decrease in inequality. Additionally, there was a shift in population share to medium low technology from the other three groups. Table 5.5 which gives the same information for two technology groups, just intensifies the previous outcomes. The more disaggregated groups we constructed, between group inequality faded away. Finally, we see that the Turkish manufacturing sector was characterized by low technology and the weight of low technology increased both in population share and income share. The decrease in wage inequality in LT in absolute terms was greater than the increase in inequality in HT.

Table 5.4: Evolution of Theil Index: Technology Level

	GE(1)		Pop. Share		Income Share		Mean Wage	
Technology	**2004**	**2015**	**2004**	**2015**	**2004**	**2015**	**2004**	**2015**
HT	0.1792	**0.1899**	0.0150	0.0147	0.0209	**0.0215**	2.5536	3.7664
MHT	0.1267	**0.1328**	0.2078	0.1926	0.2402	0.2274	2.1189	3.0302
MLT	0.1390	0.1223	0.2312	**0.2874**	0.2409	**0.2971**	1.9108	2.6521
LT	0.1115	0.0965	0.5460	0.5053	0.4979	0.4540	1.6719	2.3050
Theil (between)	0.0058	**0.0072**						
Theil (within)	0.1232	0.1144						

Source: Author's own calculations.

Table 5.5: Evolution of Theil Index: Aggregated Technology Levels

	GE(1)		Pop. Share		Income Share		Mean Wage	
Technology	**2004**	**2015**	**2004**	**2015**	**2004**	**2015**	**2004**	**2015**
HT	0.1321	**0.1395**	0.2228	0.2073	0.2611	0.2490	2.1482	3.0824
LT	0.1224	0.1090	0.7772	**0.7927**	0.7389	**0.7510**	1.7249	2.4309
Theil (between)	0.0041	**0.0051**						
Theil (within)	0.1250	0.1166						

Source: Author's own calculations.

The other aspect that we dwell on is the skill quantification using occupations of ISCO08 classification which ranks occupations with respect to both skill level and collar type. Our first aim is to insight into how the components of skill evolved from 2004 to 2015 and to discover how those occupations were located in the Turkish manufacturing sector. Grey shaded rows correspond to high skilled occupations in Table 5.6.

Table 5.6: Evolution of Theil Index: Occupations

	GE(1)		Pop. Share		Income Share		Mean Wage	
Occupations	**2004**	**2015**	**2004**	**2015**	**2004**	**2015**	**2004**	**2015**
Managers	0.1350	0.0967	0.0179	**0.0258**	0.0383	**0.0606**	3.9342	6.0141
Professionals	0.1409	0.1127	0.0154	**0.0262**	0.0301	**0.0567**	3.5849	5.5570
Technicians	0.1378	0.1093	0.0573	**0.0693**	0.0762	**0.0960**	2.4371	3.5557
Clerical	0.1318	0.0916	0.0420	**0.0476**	0.0532	**0.0540**	2.3211	2.9148
Services	0.0892	**0.0994**	0.0350	**0.0365**	0.0326	0.0319	1.7100	2.2440
Nature	0.0789	0.0289	0.0015	0.0009	0.0012	0.0008	1.5528	2.1753
Craft	0.1097	0.0826	0.4069	0.3874	0.3669	0.3522	1.6531	2.3331
Plant	0.0930	0.0579	0.3312	0.2563	0.3229	0.2279	1.7872	2.2817
Elementary	0.0881	0.0540	0.0929	**0.1501**	0.0785	**0.1199**	1.5494	2.0501
Theil (between)	0.0219	**0.0420**						
Theil (within)	0.1071	0.0796						

Source: Author's own calculations.

For each occupation except Services and Sales Workers, witnessed a decline in group Theil index. Nature, namely Skilled Agricultural, Forestry and Fishery Workers, was the most equally paid occupation for both years which also captured the least share from the manufacturing sector in terms of population and income. Professionals was the most unequally paid occupation while Technicians and Associated Professionals was the second; and Managers was the third most unequal group. The Turkish manufacturing sector was characterized mostly by Craft and Related Trades Workers and Plant and Machinery Operators and Assemblers occupations. Their ratio decreased to 64% in 2015 from 74% in 2004 and the greatest share was grabbed by Elementary Occupations around 5.7%. Skilled Agricultural, Forestry and Fishery Workers was too small to be considered in that perspective. Between occupations, wage inequality was much more evident than between industry wage inequality. The same trend in between group inequality held here as well, so the deterioration of inequality between occupations increased to 0.042 from 0.0219. Alleviation in within group inequality was not unexpected because only one occupation out of 9 occupations had worse wage inequality in 2015.

When Thiel index was constructed for skill level within the context of white – blue collar, for each skill group, we witnessed recovery and the rate of recovery increased as we had moved downward first from white collar to blue collar then high skilled to low skilled in Table 5.7. The level of inequality within each group was governed by whether it pertained to high skilled or low skilled side of the occupations. High skilled white collar and high skilled blue collar were at the top of the wage inequality list and the decline in Theil indexes was relatively limited compared to low skilled white collar and low skilled blue collar. 51% of the workers in the Turkish manufacturing sector was labelled as high skilled but only 21% belonged to white collar side. Blue collar ratio reduced to approximately 79% from 83% and three-fourth of that decline was absorbed by HSWC. Within group wage inequality was in association with the general tendency; however, there was a remarkable surge in between group inequality. Theil indexes for two skill levels reinforced the results of Table 5.7. Yet, the decrease in HS wage inequality remained limited in comparison LS.

Table 5.7: Evolution of Theil Index: Skill Level

	GE(1)		Pop. Share		Income Share		Mean Wage	
Skill Level	**2004**	**2015**	**2004**	**2015**	**2004**	**2015**	**2004**	**2015**
HSWC	0.1617	0.1365	0.0906	**0.1213**	0.1447	**0.2132**	2.9275	4.5114
HSBC	0.1096	0.0825	0.4084	0.3883	0.3682	0.3530	1.6528	2.3327
LSWC	0.1268	0.1027	0.0770	**0.0840**	0.0858	**0.0859**	2.0434	2.6237
LSBC	0.0937	0.0579	0.4241	0.4064	0.4014	0.3478	1.7351	2.1962
Theil (between)	0.0168	**0.0345**						
Theil (within)	0.1122	0.0872						

Source: Author's own calculations.

Table 5.8: Evolution of Theil Index: Aggregated Skill Level

	GE(1)		Pop. Share		Income Share		Mean Wage	
Skill	**2004**	**2015**	**2004**	**2015**	**2004**	**2015**	**2004**	**2015**
HS	0.1545	0.1505	0.4989	**0.5096**	0.5128	**0.5663**	1.8842	2.8512
LS	0.1014	0.0692	0.5011	0.4904	0.4872	0.4337	1.7825	2.2694
Theil (between)	0.0004	**0.0064**						
Theil (within)	0.1286	0.1152						

Source: Author's own calculations.

We track the same approach to five educational categories within that framework, college graduates were the only group suffering from escalating inequality. The manufacturing sector consisted of better-educated workers in 2015. There was a dramatic decrease in the share of below primary education from 52% to 35%. Regular high school lost its weight as well and turned out to be having the lowest share in 2015. Vocational high school strengthened its position according to high school and college enjoyed the highest increment proportionately. On the other hand, a quarter of the entire workers in our sample in 2015 had primary school degree and as time passed we expected that PS would surpass below-PS owing to 8-year compulsory education enactment.

Table 5.9: Evolution of Theil Index: Education Level

	GE(1)		Pop. Share		Income Share		Mean Wage	
Education	**2004**	**2015**	**2004**	**2015**	**2004**	**2015**	**2004**	**2015**
Below_PS	0.0860	0.0566	0.5230	0.3548	0.4658	0.3041	1.6328	2.1993
PS	0.1144	0.0687	0.1704	**0.2576**	0.1549	**0.2096**	1.6668	2.0879
HSC	0.1391	0.0890	0.1117	0.0892	0.1196	0.0904	1.9626	2.5991
VHS	0.1284	0.0900	0.1448	**0.1814**	0.1699	**0.1990**	2.1506	2.8150
COL	0.1537	**0.1628**	0.0501	**0.1170**	0.0898	**0.1969**	3.2874	4.3195
Theil (between)	0.0190	**0.0320**						
Theil (within)	0.1100	0.0896						

Source: Author’s own calculations.

6. COUNTERFACTUAL ANALYSES

To place the discussion in context, we devote this section to imposed technology shock in the form of SBTC and GPT on existing wage distributions and check how counterfactual wage distributions depart from the original distributions. Through the agency of that rationale, "what would happen if…?" type questions can be answered and potential trajectories of wage inequality mentioned in descriptive statistics of Section 5 can be explored. Subsection 6.1 explains the theoretical framework of DiNardo *et al*. (1996) semiparametric approach and how the basic model is reformulated in accordance with the domain of the study. Results derived from counterfactual wage distributions and their comparisons with the current states are discussed in Section 6.2.

6.1. SEMIPARAMETRIC APPROACH OF DINARDO, FORTIN AND LEMIEUX (1996)

Dinardo *et al*. (1996) published an *Econometrica* paper with the name of "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach" and later their methodology is adopted by several papers for various wage issues such as Bell and Pitt (1998), Butcher and Dinardo (2002), Eberth (2005), Kambayashi, Kawaguchi and Yokoyama (2008), Autor, *et al.* (2008), Pelek (2013), Dickey (2014) and Bakış and Polat (2015) to visualize what would happen to wage distribution if some attributes are kept constant and/or others are allowed to fluctuate. Dinardo *et al*. (1996), hereinafter DFL, state that their method has in the spirit of Oaxaca (1973) decomposition but differentiates into an important starting point: instead of concentrating on means alone, attention is directed at the complete distribution of wage. Thus, the DFL investigates wage inequality from many aspects that additionally, empowers us to analyze the influences of a variety of factors on wage distributions. To the best of our knowledge, there are only two Turkish implementations of the DFL approach, belong to Pelek (2013) to especially account for minimum wage hike of 2004 and Bakış and Polat (2015) for overall wage inequality, which again have similar outcomes for minimum wage rise of the year 2004.

The DFL method is basically as follows. Consider each observation as a vector (w,z,t) where w is wage, z is the individual attributes and t is the date. Each individual observation belongs to a joint distribution $F(w,z,t)$ and this joint distribution of w and z at one point in time is conditional on date $F(w,z\,|\,t)$. It can be conditional on any other attributes such as minimum wage, union, etc. which are most widely used in the empirical literature.

To put it more explicitly, the density of wages at one point in time, $f(w|t)$ can be written as the integral of the density of wages conditional on a set of individual attributes at a certain time t_w, $f(w\,|\,z,t_w)$ over the distribution of individual attributes $dF(z\,|\,t_z)$ at time t_z.

$$\begin{aligned} f(w|t) &= \int_{z\in\Omega_z} f(w\,|\,z,t_w=t)\,dF(z\,|\,t_z=t) \\ &\equiv f(w\,|\,z;t_w=t,t_z=t) \end{aligned} \qquad [6.1]$$

Let's assume that $f(w\,|\,z,t_w=2015,t_x=2015)$, such an expression means the actual wage distribution with the 2015 year's prices and characteristics. $f(w\,|\,z,t_w=2015,t_x=2004)$ represents the density of wages that would have prevailed in 2015 while the distribution of individual attributes remained constant as it was in 2004, $dF(z\,|\,t_z=2004)$. That information can be written as the following equation:

$$\begin{aligned} f(w\,|\,z,t_w=2015,t_z=2004) &= \int f(w\,|\,z,t_w=2015)\,dF(z\,|\,t_z=2004) \\ &= \int f(w\,|\,z,t_w=2015)\Psi_z(z)\,dF(z\,|\,t_z=2015) \end{aligned} \qquad [6.2]$$

where $\Psi_z(z)$ is the reweighting function defined as,

$$\Psi_z(z) = dF(z \mid t_z = 2004) / dF(z \mid t_z = 2015) \qquad [6.3]$$

and Equation [6.3] can be written in a more explicit form as Equation [6.4]:

$$\Psi_z(z) = \frac{dF(z \mid t_z = 2004)}{dF(z \mid t_z = 2015)} = \frac{\dfrac{dF(t_z = 2004 \mid z)dF(z)}{dF(t_z = 2004)}}{\dfrac{dF(t_z = 2015 \mid z)dF(z)}{dF(t_z = 2015)}} \qquad [6.4]$$

This reweighting function can be obtained by estimating the conditional probability generally using a Probit model controlling for individual attributes that are relevant for wage equation such as education, age, occupation, industry, etc. Therefore, reweighting function can be estimated with the following expression after Bayes' rule is applied (Dinardo *et al.*, 1996):

$$\Psi_z(z) = \frac{\Pr(t_z = 2004 \mid z)}{\Pr(t_z = 2015 \mid z)} \cdot \frac{\Pr(t_z = 2015)}{\Pr(t_z = 2004)} \qquad [6.5]$$

Finally, we can draw counterfactual densities with the weighted kernel method using the Equation [6.6]:

$$\hat{f}(w) = \sum_{i=1}^{n} \frac{\Psi}{h} K\left(\frac{w - W_i}{h}\right) \qquad [6.6]$$

where h is the bandwidth which controls the smoothness of the estimate and $K(.)$ is the kernel function (Dinardo *et al*. 1996). The kernel function is chosen as Gaussian kernel to stay in harmony with the DFL. Wang and Wang also (2007: 2) mention that "there is very little to choose between various kernels on the basis of mean integrated square error" for computational considerations. Weights Ψ are HLFS "sample weights multiplied by usual work hours of work and normalized to sum one." (Dinardo *et al*. 1996: 1009). The optimal bandwidth for those weighted density estimates is selected as 0.065 as the DFL.

We use the DFL semiparametric method to uncover the effects of imposed technology shocks to wage distribution and draw some conclusions for the SBTC literature. The contribution of this dissertation to the literature is from the empirical side by adding skill and technology dimensions in the counterfactual method to reflect a technology improvement that pretends to skill biased. For instance, we search for answer to such question: what would be the wage distribution if the individual attributes had increased to high technology manufacturing sectors level while they had been paid according to the wage schedule observed in low technology manufacturing sectors? Cross skill and technology analyses in terms of occupation and industry level are the main motivation of using the DFL technique.

Therefore, the set of equations from [6.2] to [6.4] is replaced with the set of equations from [6.6] to [6.8]. Put it differently, the point of view we want to capture is the effects of different skill and technology levels instead of date or other attributes. Previous equations are re-estimated as follows.

This joint distribution of w and z is conditional on u is $F(w,z|u)$, where u is technology (skill) levels. Then, we write it as the integral of the density of wages conditional on a set of individual attributes at low technology sectors (low skilled workers) u_{low}, $f(w|z,u_{low})$ over the distribution of individual attributes $dF(z|u_{high})$ at sector (labor market) u_{high}. Equation [6.2] can be re-parametrized as Equation [6.6]:

$$f(w|z,u_t = low, u_t = high) = \int f(w|z,u_t = low)dF(z|u_t = high)$$
$$= \int f(w|z,u_t = low)\Psi(z)dF(z|u_t = high) \quad [6.6]$$

On the one hand, $f(w|z,u_t = low, u_t = low)$ means the actual wage distribution with low technology's (skill's) prices and characteristics. On the other hand, $f(w|z,u_t = low, u_t = high)$ represents the density of wages that would have prevailed in low technology (skill) while the distribution of individual attributes remained constant as it was in high technology (skill), $dF(z|u_t = high)$. $\Psi(z)$ is the reweighting function defined as;

$$\Psi(z) = dF(z|u_t = low)/dF(z|t_z = high) \quad [6.7]$$

and we re-write Equation [6.7] can be written more explicitly as Equation [6.8].

$$\Psi(z) = \frac{\Pr(u_t = low|z)}{\Pr(u_t = high|z)} \cdot \frac{\Pr(u_t = high)}{\Pr(u_t = low)} \quad [6.8]$$

The reweighting function is estimated with the Probit model by controlling for potential experience, square of potential experience, tenure, education, occupation, industry, firm size, age cohorts, having social security, and marital status. Potential experience means total potential years in the labor market, age minus the age at which he first entered the job market. Entrance age to the job market is estimated according to years of schooling, while tenure is estimated by subtracting relevant year from the starting year of employment at the current job. Occupation is based on ISCO08 at one-digit for 9 main categories and industries are listed as NACE Rev.2 at the two-digit level for 34 industry categories. Firm size determines whether an individual works at a firm having more than 50 employees or less. Age cohorts are constructed at 5-year intervals from 15 to 64. There are 10 categories for the interval 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, and 60-64. Registration to the social security system and marital status are also considered as dummy variables. Marital status is scaled down into two categories: married or not. Education can only have 5 categories to establish consistency among different years of HLFSs: below the primary school, primary school, high school, vocational high school, and college. Below the primary school includes illiterate, literate without schooling and 5-year primary schooling. Primary school represents 8-year compulsory education. Having two different high school types can also provide some useful information about the importance of direct vocational education in terms of wage inequality. Finally, the college includes 2-year college and higher than college degrees.

Furthermore, we have room for maneuver to exclude some of the conditional variables from the set of individual attributes such as education, occupations, or industries. In case of a desire to keep an attribute at its actual level, weight should be estimated using the Probit model without that variable.

6.2. EMPIRICAL RESULTS

This part contains the main counterfactual results of the DFL applications. The way we scrutinize the data into various diffractions is listed as skill and technology level. However, we also check the results that are conditional on year to gain a broad comprehension of how the labor market structure changed from 2004 to 2015. In addition to them, topics of education, occupation, and industry are also discussed as the subheads of the analyses. We draw counterfactual densities according to technology and skill dimensions and give the answer of that question: what would be the wage distribution if some attributes had remained the same but workers had been paid according to the actual wage schedule? On the other hand, that technique allows us to change over the aforementioned question to a different form: what would be the wage distribution if some attributes had remained the same while we had released others to change but workers still had been paid according to their own wage schedule.

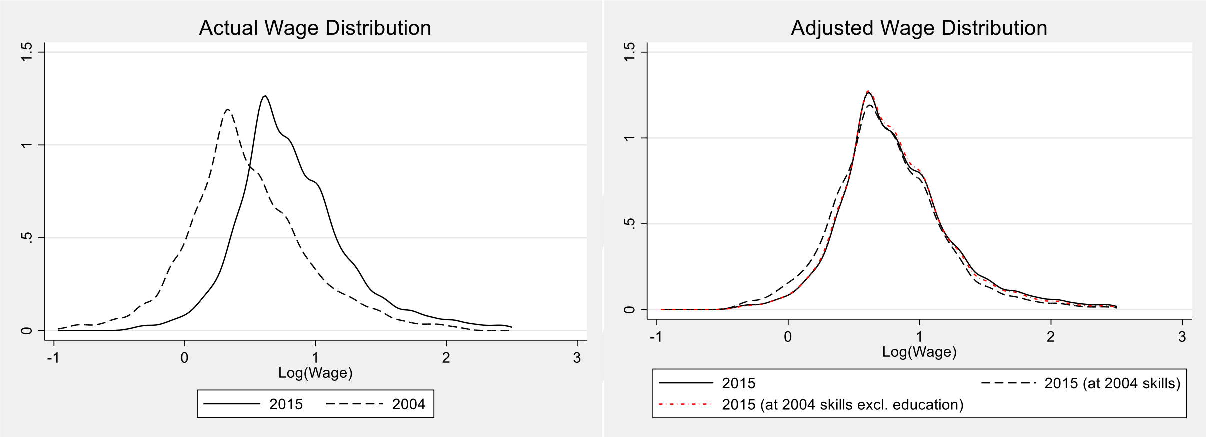
Graphs in this subsection are constructed using the natural logarithm of real hourly wage and straight density lines correspond to actual wage distributions while dashed lines correspond to counterfactual wage distributions. Both actual and counterfactual wage densities are evaluated at 200 values to simplify the kernel density estimation. Increasing the number of values does not generate different patterns or significant deviations in the wage dispersion.

Estimation results of Probit models can be found in the Appendix, Table B1 and Table B2. Weighted kernel densities are obtained for counterfactual densities by substituting weights found in Equation [6.8] into Equation [6.5]. We start with a conventional analysis of years to debate over the transformation of wage distribution from 2004 to 2015. The first part of Graph 6.1 visualizes the real wage distributions of years 2004 and 2015 and those years have similar patterns although there is a tendency to improve in wages in 2015 due to the rightward shift of the distribution. Part (b) of Graph 6.1 answers what happens if workers would have 2004 attributes while they were paid according to 2015 prices. If individual attributes remained the same in 2015 as in the case of 2004, lower percentiles would get higher wages while upper percentiles would get lower wages. The height of the counterfactual wage distribution shrinks as well. Nevertheless, when we do not let the education level to change, counterfactual wage distribution nearly matches with the actual distribution. Therefore, to account for the difference between various wage distributions, wage dispersions and change in wage dispersions tables are constructed. Check Table A6 in the Appendix for their values in levels.

Table 6.1 summarizes log wage dispersions in levels for i) 2004, ii) 2015, iii) 2015 with 2004 attributes and iv) 2015 with 2004 attributes but without education. Wage gaps for all groups decreased from 2004 to 2015 and those shrinkages intensified when we had imposed 2004 attributes to 2015 except without education case. It could be stated that upper tail and lower tail had different responses to educational categories. When 2015 education levels were kept constant, lower tail wage inequality slightly improved as the wage dispersion moved to 0.401 from 0.418. On the other hand, if we transform 2004 education levels to 2015, lower tail wage inequality soared up to 0.453 which was much higher than the original situation. The upper tail of the wage distribution, on the contrary, followed a consistent path. In each counterfactual case, wage dispersions narrowed but 2004 education levels had a greater impact on the recovery. Clearly, more work needs to be done to assess the diverse trajectories of tails but one potential reason might stem from the increase in the general education levels. The lower tail might benefit from that educational progress as they have more room for personal development and escalation from their existing echelon.

Graph 6.1: Actual and Adjusted Wage Distributions: 2004 and 2015

(a) (b)



Source: Author's own calculations.

Table 6.1: Log Wage Dispersion with respect to Years

	p90-p10	p90-p50	p50-p10	p75-p25	p99-p01
2004	1.133	0.662	0.471	0.540	2.423
2015	1.029	0.610	0.418	0.488	2.301
2015 with 2004 attributes	1.011	0.558	0.453	0.506	2.249
2015 with 2004 attributes without education	0.976	0.575	0.401	0.488	2.197

Source: Author's own calculations.

Changes in low wage dispersions between interested groups for 2004 and 2015 are listed in Table 6.2. During the period considered, actual wage gaps for all percentile groups decreased from 2004 to 2015 and upper and lower tail inequalities diminished equally. If we transform 2004 attributes into 2015, inequality tended to decrease less, and even for lower tail wage gap increased by 0.035. When we relax the assumption and let the education stays at the 2015 level, the general tendency is much closer to the actual difference between 2015 and 2004. Thus, education seemed to be a strong factor to improve inequality. The last row of Table 6.2 confirms that the same characteristics in 2004 except education which induced narrow gaps for all wage dispersions except the upper tail. But for this particular case, the decrease in wage inequality had a cost: low level of wages directly translated into lower wage inequality. See Table A5 in the Appendix for wage level values. It is logical as well because of the "sticky floor" effect. Workers at the bottom of the wage distribution were already in a desperate position with their wage levels and individual specific factors or labor market conditions could not further lower their wages below minimum wage or subsistence wage levels. Although we digress from the core of the topic, according to Table A5, there are some cases in the lower end of the wage distribution that exhibited lower real hourly wages than lower real hourly minimum wage. That might be the evidence of informality in the manufacturing labor market but to place that claim in a concrete context requires more work. Therefore, we hesitate to use assertive words on that issue for now. As workers at the lower tail of the wage distribution lose their bargaining power, they collapse into that sticky floor. Eventually, wage inequality seems to be diminished while the whole group earns lower wages. Besides, the distance between 90th percentile and median wage increased by 0.017.

Table 6.2: Change in Log Wage Dispersion with respect to Years

Year	Gap	Δ
2015 - 2004	p90-p10	-0.105
	p90-p50	-0.052
	p50-p10	-0.052
	p75-p25	-0.052
	p99-p01	-0.122
2015 with 2004 attributes - 2015	p90-p10	-0.017
	p90-p50	-0.052
	p50-p10	0.035
	p75-p25	0.017
	p99-p01	-0.052
2015 with 2004 attributes without education - 2015	p90-p10	-0.052
	p90-p50	-0.035
	p50-p10	-0.017
	p75-p25	0.000
	p99-p01	-0.105
2015 with 2004 attributes without education - 2015 with 2004 attributes	p90-p10	-0.035
	p90-p50	0.017
	p50-p10	-0.052
	p75-p25	-0.017
	p99-p01	-0.052

Source: Author's own calculations.

From now on, high skill – low skill and high technology – low technology discriminations are identified to test how the skill biased technical change affects the wage distribution. That procedure depends upon three important postulations, which are distilled from Section 2 with firm theoretical reasons:

I) "New technologies are not complementary to skills by nature, but by design" (Acemoglu, 1998: 1056), and because of higher capital-labor ratio in high technology industries, new technologies are developed for those industries and their utilization requires a minimum skill level to be implemented by workers and absorptive capacity is limited by the current skill level of a worker. Transferring attributes of high technology workers to the low technology workers (with education) acts as an "appropriate technology" shock, which is naturally skill biased.

II) The previous postulation, along the same line, can be applied to the high skill and low skill distinction, as well. High skilled workers are implicitly more productive and the imposition of individual attributes of high skilled labor to low skilled labor naturally acts if as they experienced a kind of productivity shock triggered by a technology shock that is intrinsically skill (unskilled) biased.

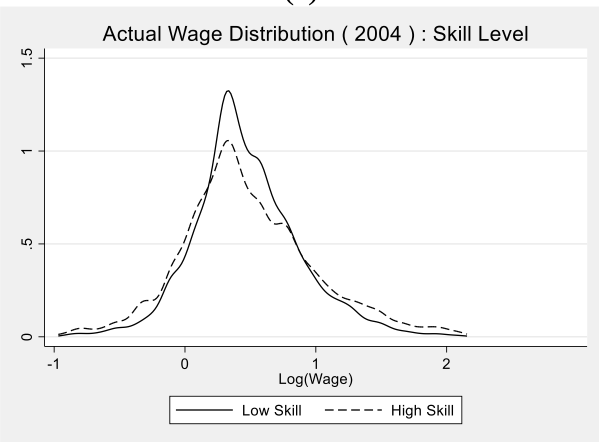
III) If we keep the education level of low skilled workers constant while imposing other high skill attributes, that acts as a "general purpose technology". The education level of low skill workers does not increase while they might have higher abilities according to their education levels. Because nobody knows how to use new GPT at first and in the process of time, it is started to be used first by highly educated low skilled labor, which is also more restricted in that group. Adoption and implementation procedure of new technology might pave the way for an increase in wage inequality even in case of increased supply of skilled labor, through general purpose technology, but since the "factor" that makes labor skilled is education and we keep it same; therefore, such imposition should not alter wage distribution, particularly for low skilled labor, significantly like SBTC.

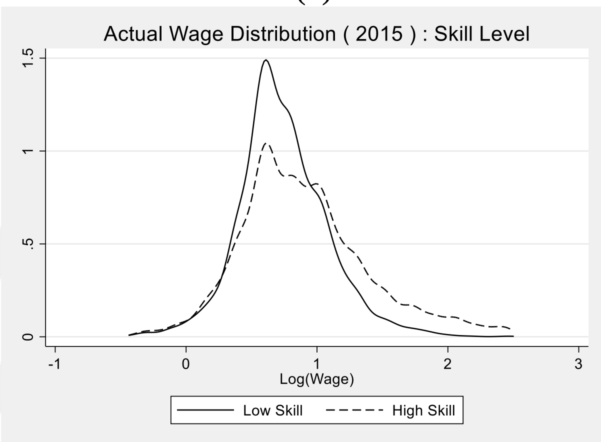
To understand the evolution of real wage within skill groups and between years, Graph 6.2 is drawn. Considering the aforementioned postulations, counterfactual wage distributions are constructed first at skill level in Graph 6.3. To make all graphs comparable, both the x-axis and the y-axis are scaled identically. However, in cases where differences between wage distributions, especially in counterfactual densities, are not overt, percentiles of the log wage distributions are tabulated to figure out changes. Numbers in tables, in this section, are rounded to three decimals. Thus, the sum of the upper and lower tails may not be exactly equal to the overall inequality. Graphs below show actual wage distributions for skill levels.

The difference in the median wages across aggregated skill group is greater than the difference in tails as seen in Graph 6.2. At the right tail, high skill has more apparent humps than low skill, probably traces of the wage polarization. The smoothness of those humps depends on the specification of kernel function and bandwidth selection, but the overall shape does not sensitive to those selections. Nonetheless, within and between skill group wage dispersions are tabulated in Table 6.3. Despite the salient mitigation in all wage dispersion at within skill group, high skill diverged from low skill in terms of wage inequality during that twelve year-period due to limited amelioration of within high skill wage dispersion. In addition to that, the decline in lower tail wage inequality was less than the decline in upper tail wage inequality for LS. The exact opposite situation happened for HS.

Graph 6.2: Actual Wage Distributions: LS and HS

(a) (b)





Source: Author's own calculations.

Table 6.3: Log Wage Dispersions: LS and HS

Skill	Gap	2004	2015	Δ
HS - LS	p90-p10	0.267	0.414	0.147
	p90-p50	0.188	0.281	0.093
	p50-p10	0.078	0.133	0.055
	p75-p25	0.141	0.177	0.036
	p99-p01	0.455	0.665	0.210
LS_2015 - LS_2004	p90-p10	1.005	0.813	-0.191
	p90-p50	0.565	0.458	-0.107
	p50-p10	0.440	0.355	-0.085
	p75-p25	0.487	0.414	-0.073
	p99-p01	2.135	1.804	-0.331
HS_2015 - HS_2004	p90-p10	1.272	1.227	-0.044
	p90-p50	0.754	0.739	-0.014
	p50-p10	0.518	0.488	-0.030
	p75-p25	0.628	0.592	-0.036
	p99-p01	2.590	2.470	-0.121

Source: Author's own calculations.

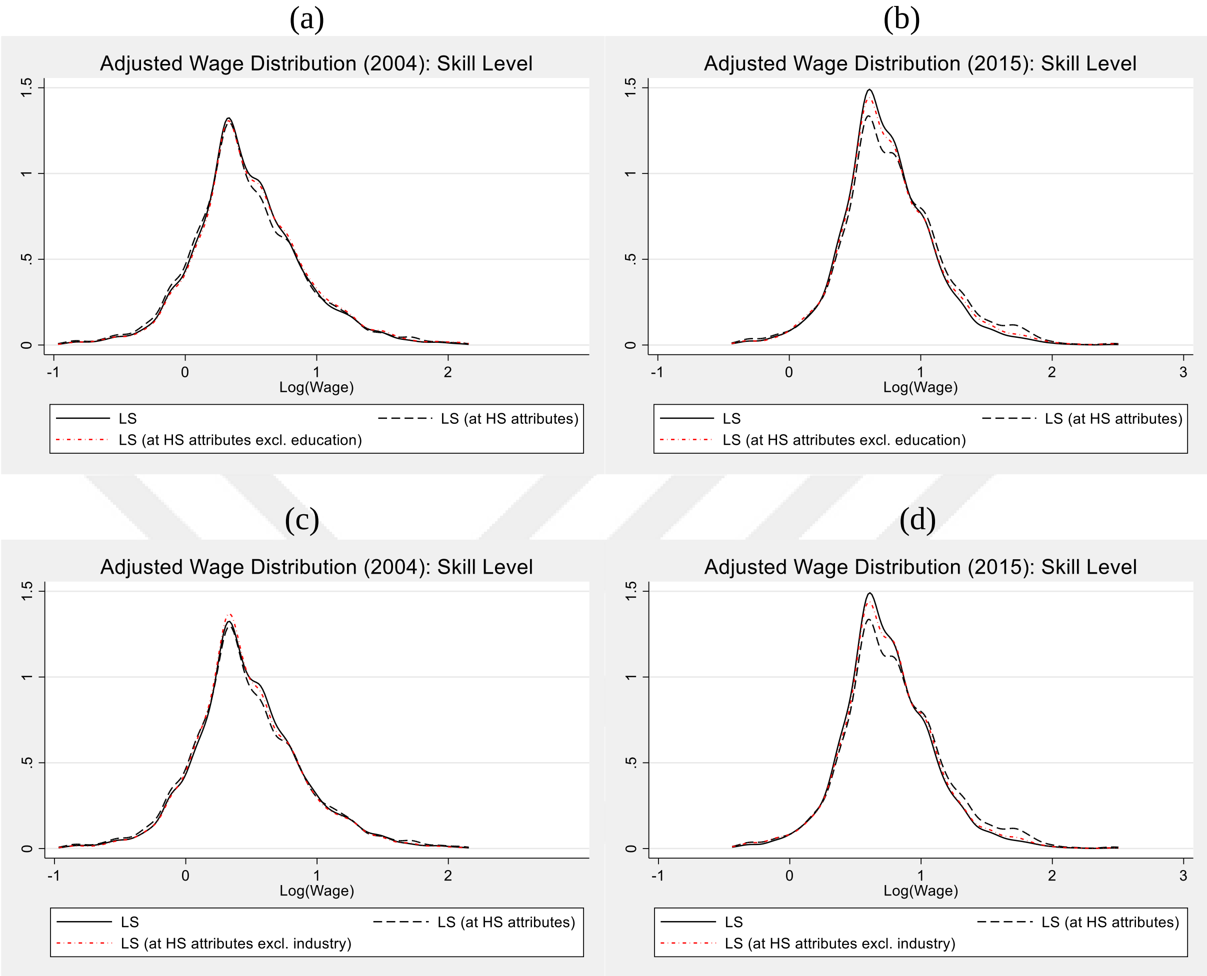
After a general inspection at the skill group level, we can look at what happens to the wage distribution when a hypothetical skill biased technology comes up. Throughout this subsection, dashed density lines depicture counterfactual distributions. Black dashed line is for what happens if low skill or low technology wage earners would have high skill or high technology attributes and red dashed line is for what happens if low skill or low technology wage earners would have high skill or high technology attributes, except education level, occupation or sector information. Keeping in mind those three different wage distributions, Graph 6.3 part (a) and (b) indicate first, what happens if low skill wage earners would have high skill attributes and secondly, what happens if low skill wage earners would have high skill attributes except education level. The first imposition acts as if there would be a technological improvement in their productivity caused by skill bias change in technology for low skilled workers and the second imposition acts as if there would be a neutral technological improvement for low skilled workers, again.

By doing so, we can also see, as a by-product, what can be the main factors specific to high skill groups that determine the deviation from actual wage density. Some attributes, so then, can be discarded to account for their relative importance. Education and NACE Rev.2 two-digit manufacturing industries are chosen as two agents that implicitly carry skill-complementary properties, so weights are re-estimated for all variables apart from education and industries, individually. All dashed lines in graphs are weighted kernel density estimations in accordance with that procedure. To test the power of high skilled workers' education transmitted to low skill, the education level of low skill workers will be preserved. The underlying rationale is this, education stays at levels in the low skill or low technology industries because education is one of the factors that cannot be changed immediately when an individual enters the job market. We can combine results in Table 6.4 to have a better understanding of the graphs because; deviations from the actual wage distribution remained limited visually, in particular in the lower end of the wage distribution.

In Graph 6.3 (a), wax and wane of the counterfactual wage distribution resemble to actual distribution in 2004, there are only two divergent points: i) the former spreads over a wider range and ii) the hump on the actual line is truncated with the injection of high skill attributes into low skilled workers. In Graph 6.3 (b), the overlapping structure turns out to be invalid after the lower tail, and the influences of counterfactual high skill strengthen for the median wage with its neighborhood and also for the upper tail. Nevertheless, for 2015, such skill biased technical change for the low skilled category would shift the distribution to the right-hand side and would exacerbate wages in opposition to low-wage earners. As a result, the top of the distribution repressed and upper percentiles deviated from the real distribution, and approached to counterfactual wage distribution in 2015. Finally, from 2004 to 2015, the upper tail became more sensitive to skill-biased changes. Almost matched densities, especially in 2004, demonstrated that the education level of high skilled workers was the main means of transmission to converge low skill wages to the high skill wages. If low skill stayed at their education level, other attributes of high skill would not help to deal with low wage and to converge first counterfactual wage levels.

Part (c) and (d) of Graph 6.3 just replicate the third case where instead of omitting education, industry information is kept at the low skill levels. Employing this, the effects of GPT shock can be re-examined. Black solid line and black dashed line are the same as the part of (a) and (b), but they are preserved to ease the comparison with previous graphs. At the end, both technological changes generate similar counterfactual wage distributions, and to refer to the difference, we draw Table 6.4 in which log wage dispersions can provide some solid basis for densities.

Graph 6.3: Counterfactual Wage Distributions at Skill Level



Source: Author’s own calculations.

Table 6.4: Log Wage Dispersions: Counterfactual HS Attributes

Skill	Gap	2004	2015	Δ
LS with HS attributes (SBTC_LS) - LS	p90-p10	0.047	0.118	0.071
	p90-p50	0.031	0.074	0.043
	p50-p10	0.016	0.044	0.029
	p75-p25	0.016	0.044	0.029
	p99-p01	0.157	0.192	0.035
LS with HS attributes without education (GPT_LS) - LS	p90-p10	0.016	0.059	0.043
	p90-p50	0.031	0.044	0.013
	p50-p10	-0.016	0.015	0.030
	p75-p25	0.000	0.000	0.000
	p99-p01	0.063	0.089	0.026
LS with HS attributes without education (GPT_LS) - LS with HS attributes (SBTC_LS)	p90-p10	-0.031	-0.059	-0.028
	p90-p50	0.000	-0.030	-0.030
	p50-p10	-0.031	-0.030	0.002
	p75-p25	-0.016	-0.044	-0.029
	p99-p01	-0.094	-0.104	-0.009
LS with HS attributes without NACE - LS	p90-p10	-0.016	0.030	0.045
	p90-p50	0.000	0.015	0.015
	p50-p10	-0.016	0.015	0.030
	p75-p25	-0.016	0.000	0.016
	p99-p01	-0.031	0.089	0.120
LS with HS attributes without NACE - LS with HS attributes	p90-p10	-0.063	-0.089	-0.026
	p90-p50	-0.031	-0.059	-0.028
	p50-p10	-0.031	-0.030	0.002
	p75-p25	-0.031	-0.044	-0.013
	p99-p01	-0.188	-0.104	0.085
LS with HS attributes without education - LS with HS attributes without NACE	p90-p10	0.031	0.030	-0.002
	p90-p50	0.031	0.030	-0.002
	p50-p10	0.000	0.000	0.000
	p75-p25	0.016	0.000	-0.016
	p99-p01	0.094	0.000	-0.094

Source: Author’s own calculations.

The first row lends some support to negative effects on low skill wages. All five wage dispersions widened and the upper tail suffered from inequality more than the lower tail, but when we look at the change in years, wage inequality in the lower tail increased more in percentage terms. Consequently, when we give low skilled wage earners to high skilled wage earners attributes, wage inequality deteriorated in low skill group; however, upper tail and lower tail had contributed to that inequality unevenly. Despite the share of lower tail in the overall inequality increased to 37.5% from 33%, the upper tail still grabbed the majority. It is possible to claim that if low skill encounters with a technology shock that increases their skill level, in other words if there is an SBTC for that group, wages within the low skill group will be more diverse; high wage earners will try to shift the wage distribution to the detriment of low wage earners.

According to the second row of Table 6.4, we can see the difference between counterfactual and actual wage distributions decreased considerably; and exclusion of education from counterfactual analysis reduced the effect of technology shock for all wage dispersions. Lower tail wage inequality rose more than the upper tail and 70% of the increase in overall wage inequality stemmed from the lower tail. Therefore, transferred high skill education, interchangeably hypothetical higher education, gave rise to narrow lower tail wage gaps. We can refer to Table 5.2 here, because according to aggregated skill grouping, the sum of COL, VHS, and HSC is 22.22 and 16.84 for HS and LS in 2015, respectively while they were 16.18 and 14.52 in 2004.

All in all, we can conclude that despite skill biased technical change increased overall wages due to the shifts in distributions to rightward as in Graph 6.3, it favored unequally for tails, increasing inequality in the upper tail further than the lower tail. On the other hand, the introduction of GPT had the opposite effect than SBTC. Change in the lower tail wage inequality nearly doubled while change in the upper tail wage inequality increased less than half. Midrange wage dispersion remained the same and the distance between the 99th and the first percentile scaled up less than overall wage gap.

The third row depicts the difference between without education case (GPT) and with education case (SBTC). Lower tail of the wage distribution seemed to be unresponsive to the kind of technology shock in terms of change in wage dispersion from 2004 to 2015. When we only refer to the third row, it can be easily misperceived that introduction of GPT had a greater power on reducing upper tail wage inequality than SBTC. In addition to that, for the purpose of comparing two technology shocks, when we look at the greater scheme, except lower tail, all other measures of wage inequality moved into the same direction: SBTC magnified inequality more than GPT; however, in comparison, GPT acted as if wage equalizer owing to restricted rise in wages. See Table A6 in the Appendix for wage levels. In the light of these considerations, we see a *pattern*: there is a trade-off between low level of wages and higher wage inequality. In the same vein, this kind of technological improvement can be regarded as general purpose technology because the ability of workers is eliminated; technology is new to all workers; innate/parental abilities may gain prominence, and productivity shock is scaled down if someone in the low technology has a lower education.

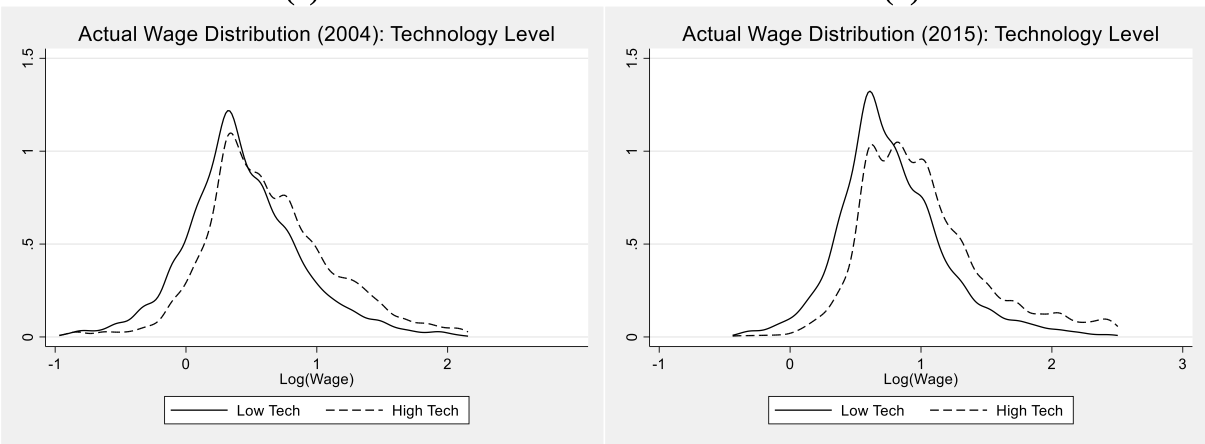
As a second step, to obtain weights through the estimation of the Probit model, we let the low skill wage earners to work in their original industries but with high skill attributes and paid according to the wage schedule observed in low skill. In other words, two-digit manufacturing industries from NACE Rev.2 10 to 33 are not controlled instead of education level as in case of part (a) and (b) in Graph 6.3. Parts (c) and (d) of the same graph demonstrate results from the eyes of manufacturing industries. Thus, the permeability of industries is implicitly put forward, and eventually, main outcomes do not differ from what has been found previously in without education case. Apart from fractional amelioration at the top of the distribution in 2004, keeping out education levels or industries at two-digit gives us the different side of the same coin in counterfactual analyses, especially for 2015. The fourth row in Table 6.4 confirms without education counterfactual results. The only difference is the bulky hike in the p99-p01 wage dispersion compared to p90-p10 with the exclusion of education counterpart. Wage dispersions and change in wage dispersions between GPT, which is estimated through the exclusion of industries, and SBTC are shown in the fifth row. They again track the same pattern as results from the second row. Wage gap for the 99th percentile and the first percentile had a gargantuan shift to 0.085 from -0.009, because the new GPT reduced wage dispersion unlike the rise caused by GPT for the same wage gap. When we look at the wage levels in Table A6, for 2004, the introduction of new GPT even lowered the wage level for the percentiles of 99, 90, 75, and 50. On the other hand, for 2015, this was only valid for the 1st percentile; and no matter the nature of technological change, wage levels increased. The last row indicates education level and in which industry you work cases, which resulted in similar impacts on wage inequality for most parts of the wage distribution, with the exception of p99-p01 dispersion which, to a large extent changed negatively by 0.094.

Parallel analyses are conducted for the first postulation as well. Therefore, first of all, new weights are estimated and then new counterfactual wage densities are drawn with respect to aggregated technology levels. High technology industries have skilled biased technology improvements and low technology industries do not necessarily witness such skill bias due to low capital-labor ratios; thus, replacement of high technical characteristics into the low technology manufacturing sector stands for skill biased technological upgrade. Graphics produced using technological caliber instead of skill level can be found in Graph 6.4 and 6.5. Table 6.5 and 6.6 replicates Table 6.3 and 6.4.

According to the new graphs, we witness that visual representation was magnified and counterfactual distributions deviated drastically from actual wage distributions. It is seen that the overall shape of the low technology wage distribution was to some extent consistent from 2004 to 2015, differences only sprang from the height and at the bottom of the distribution. Although, wage distribution of low technology sectors got shorter and stepper, median wages had more densities in 2015. Wages in high technology manufacturing sectors had a very different pattern than the low technology. First of all, the hump in 2004 converted into significant three peaks, there were two local maxima with slightly obvious troughs compared to Graph 6.2; secondly, the upper tail lost its density and squeezed in a narrow area but far end distribution gained some frequency; thirdly, the lower end of the distribution followed a slightly steeper but smoother trajectory.

Graph 6.4: Actual Wage Distributions: LT and HT

(a) (b)



Source: Author's own calculations.

Table 6.5: Log Wage Dispersions: LT and HT

Technology	Gap	2004	2015	Δ
HT - LT	p90-p10	0.110	0.177	0.068
	p90-p50	0.126	0.163	0.037
	p50-p10	-0.016	0.015	0.030
	p75-p25	0.063	0.089	0.026
	p99-p01	0.157	0.104	-0.053
LT_2015 - LT_2004	p90-p10	1.083	0.976	-0.107
	p90-p50	0.612	0.577	-0.036
	p50-p10	0.471	0.399	-0.072
	p75-p25	0.534	0.473	-0.061
	p99-p01	2.339	2.174	-0.165
HT_2015 - HT_2004	p90-p10	1.193	1.153	-0.040
	p90-p50	0.738	0.739	0.002
	p50-p10	0.455	0.414	-0.041
	p75-p25	0.597	0.562	-0.035
	p99-p01	2.496	2.277	-0.219

Source: Author's own calculations.

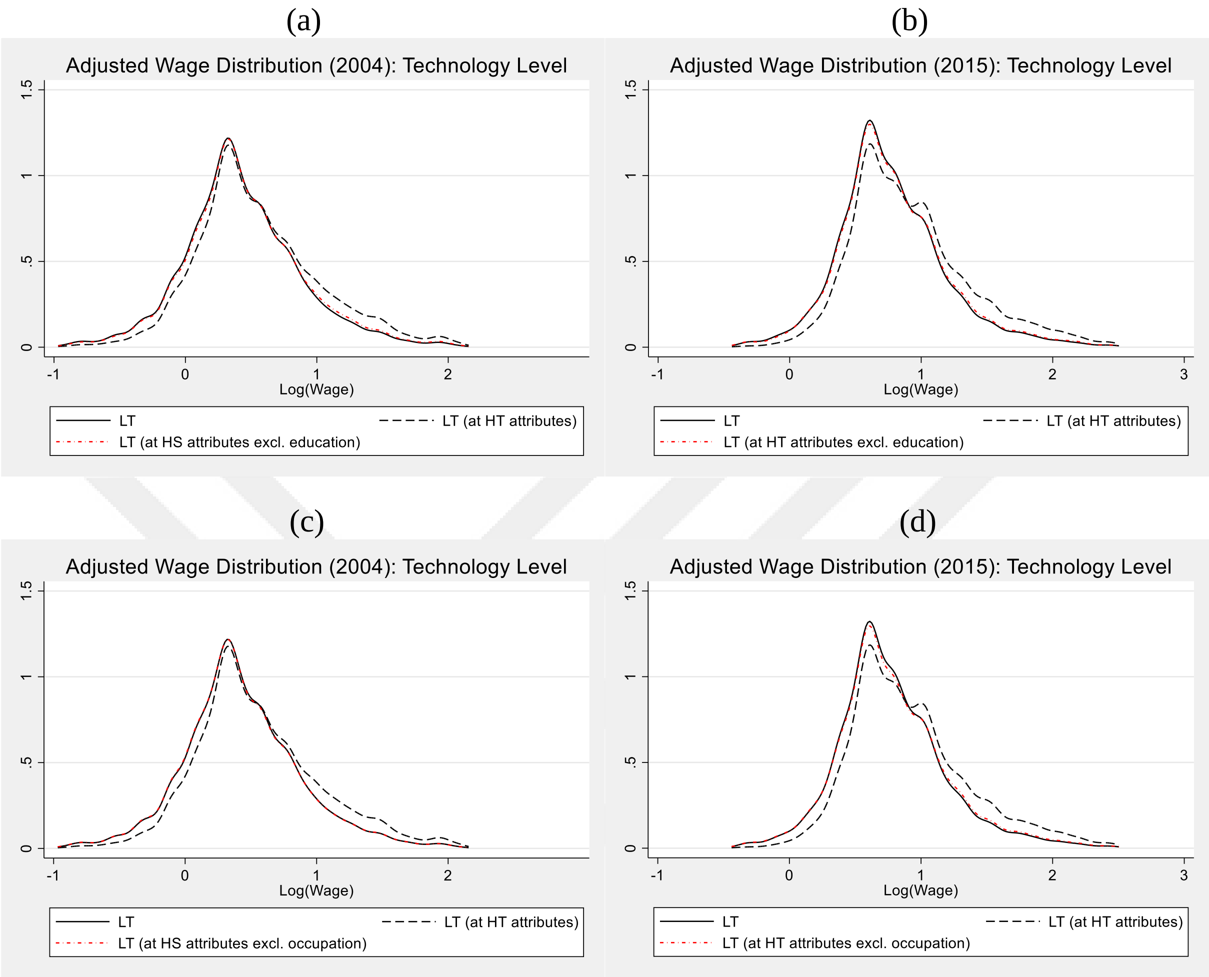
To tabulate within and between changes in wage dispersions of high – low technology sectors, Table 6.5 is drawn. The general pattern of change in wage gaps is the same as the high – low skill distinction although the magnitudes are smaller. Except for the gap between the 99th percentile and the 1st percentile, all of the dispersions enlarged, causing the divergence of high technology wages from wages earned in low technology. Upper and lower tails contributed to change in overall wage inequality more equally than the case seen in Table 6.3. In a similar way, upper tail inequality prevailed over lower tail inequality, and shares of lower tail inequality in the overall inequality for both years were too negligible compared to low skill counterparts. Therefore, low-wage earners were trapped in a narrow area; they received similar wages regardless of the technology they work in and most of the overall inequality resulted from the median and the 10th percentile gap.

When we look at the dynamics within the technology group, particularly for the low technology group, overall wage inequality declined and lower percentiles contributed to recovery strongly, nearly 2/3 of the recovery came from the lower tail. A different situation came into existence in case of high technology, upper tail wage inequality stayed at the level of 2004. For both technology groups, upper tail wage gaps spread on a larger area than lower tail wage gaps, and besides, the high technology manufacturing sector suffered from wider wage dispersions than the low technology manufacturing sector. According to our categorization, lower tail wage dispersion in 2004 was the only exception, where it is 0.471 and 0.455 in low and high technology, respectively. Another observation that can be derived from that table is about the persistence of wage inequality. Except for upper tail wage dispersion of high technology in 2015, all within group wage inequalities in terms of overall, midrange, upper tail, and lower tail decreased at different rates, despite the fact that low technology improved faster. In addition to this, the speed of the shrinkage in wage dispersion in high technology overwhelmed low technology only at the widest wage dispersion. Finally, upper tail wage inequality deteriorated even in high technology slightly from 2004 to 2015, and this was the only case that behaved against the general trend. However, we can end up with a pattern here that is also valid for high and low technology cases: upper tail wage dispersion was always greater than the lower tail wage dispersion.

After a general outlook of wage inequality at the technology dimension, we can proceed to the next step where we incorporate hypothetical technology shocks into the manufacturing sector to comprehend how wage inequalities exposed to SBTC and GPT undergo change. In order to track down changes in wage inequality, we utilize both Graph 6.5 and Table 6.6. Graph 6.5 delves into how wage distribution changes when the low technology manufacturing sector is assumed to have high technology manufacturing sector attributes. Deviation from real wage distribution was more apparent from low – high skill distinction mentioned in Graph 6.3. Skill biased technical change in the low technology sector shifted counterfactual wage distributions to right and that shift was in a similar proportion for both tails in 2004. Hence, nearly all wage earners gained a rise in their wages. On the other hand, such skill biased technical change was harmful to wage equality over the period since the density curve was repressed downward and the mode of the distribution with its neighborhood broadened. Unlike Graph 6.3, this time, polarization through the agency of local maximum spotted on the black dashed line in Graph 6.5(b) was quite salient.

In the context of GPT, we do not take into consideration education levels in high technology rather low technology maintains its own education level while other attributes which belong to high technology are imputed to the wage earners of low technology. Red dashed lines in part (a) and (b) do not clearly diverge from the black solid line; thus, as in the case of analyses based on the second postulation, clear cut results cannot be obtained for new GPT. The only visible conclusion is the barely leftward shift of the upper tail. For this reason, the necessity of a wage dispersion table still exists. Instead of education, this time, occupation is kept out of sample weight, in the Probit estimation, and in this way; we substitute weights without education with weights without occupation. Part (c) and (d) of Graph 6.5 display that counterfactual wage distribution nearly overlapped with the actual wage distribution in 2004 and the discrepancy in this counterfactual GPT was too small compared to counterfactual SBTC.

Graph 6.5: Counterfactual Wage Distributions at Aggregated Technology Level



Source: Author's own calculations.

Table 6.6: Log Wage Dispersions: Counterfactual HT Attributes

Technology	Gap	2004	2015	Δ
LT with HT attributes (SBTC_LT) - LT	p90-p10	0.126	0.148	0.022
	p90-p50	0.141	0.133	-0.008
	p50-p10	-0.016	0.015	0.030
	p75-p25	0.047	0.074	0.027
	p99-p01	0.047	0.015	-0.032
LT with HT attributes without education (GPT_LT) - LT	p90-p10	0.016	0.015	-0.001
	p90-p50	0.016	0.015	-0.001
	p50-p10	0.000	0.000	0.000
	p75-p25	0.000	0.015	0.015
	p99-p01	0.031	0.044	0.013
LT with HT attributes without education (GPT_LT) - LT with HT attributes (SBTC_LT)	p90-p10	-0.110	-0.133	-0.023
	p90-p50	-0.126	-0.118	0.007
	p50-p10	0.016	-0.015	-0.030
	p75-p25	-0.047	-0.059	-0.012
	p99-p01	-0.016	0.030	0.045
LT with HT attributes without occupation - LT	p90-p10	0.000	0.030	0.030
	p90-p50	0.000	0.015	0.015
	p50-p10	0.000	0.015	0.015
	p75-p25	0.000	0.015	0.015
	p99-p01	0.016	0.044	0.029
LT with HT attributes without occupation - LT with HT attributes	p90-p10	-0.126	-0.118	0.007
	p90-p50	-0.141	-0.118	0.023
	p50-p10	0.016	0.000	-0.016
	p75-p25	-0.047	-0.059	-0.012
	p99-p01	-0.031	0.030	0.061
LT with HT attributes without education - LT with HT attributes without occupation	p90-p10	0.016	-0.015	-0.030
	p90-p50	0.016	0.000	-0.016
	p50-p10	0.000	-0.015	-0.015
	p75-p25	0.000	0.000	0.000
	p99-p01	0.016	0.000	-0.016

Source: Author’s own calculations.

Skill biased technical change in the form of counterfactual high technology shifted original low technology densities to a larger extent. However, to make a yearly comparison, Table 6.6 is constructed including the magnitudes of and changes in wage dispersions. From the first row, where the difference of wage distribution after SBTC and the original wage distribution is placed, we see that such a skill bias technology inclined to moderate barely upper tail wage inequality while lower tail inequality gap to double. Besides, the rise in overall inequality was directly developed out of the lower tail. When low technology workers were imposed to have attributes of high technology workers except education level, in other words we assume this imposition acts as if there would be a general purpose technology. At the end, there was no significant change in the wage dispersions between counterfactual and actual low technology densities. Overall, upper tail and lower tail wage gaps continued to be at their 2004 level in 2015 as well; midrange wage gap and p99-p01 gap widened.

On the one hand, when we treat GPT as developed out of education exclusion, wage levels increased for all interested percentiles; on the other hand, those increases were much limited compared to the increase in wage levels at the upper percentiles of GPT introduced low technology counterparts. All in all, skill and technology dimensions have different responses to the new GPT shock in terms of yearly changes. Although within yearly shifts from 2004 to 2015 in the counterfactual wage distributions were much more distinctive in low - high technology cases; however, changes in those shifts persisted, leading to no effect on the wage dispersion. p75 – p25 and p99 – p01 wage dispersions only experienced tenuous deterioration. The relative performance of GPT and SBTC can be understood from the third row. Different from the rise in upper tail wage inequality, both lower tail and overall wage inequalities decreased.

Unlike the without education case, if the occupation is discarded, wage inequality increased slightly and both tails had equal shares in that increase. However, we need to be suspicious of commenting on those increases because new GPT (without occupation case), actually did not alter the original wage distribution, and probably since we evaluate counterfactual analyses at 200 values, wage levels of percentile match for both wage distributions. That result might stem from the weakness of GPT quantification by keeping occupation as the main determinant or simply just because of the number of values considered at the construction of counterfactual wage distribution. In the light of this information, the numbers in the fourth row of Table 6.6 tell us that from 2004 to 2015, counterfactual wage distribution maintained its shape with symmetric expansion. The fifth row of Table 6.6.

compares that new GPT and SBTC. Overall inequality worsened by 0.007 and the upper tail tried to pull up overall wage inequality by 0.023 while the lower tail alleviated by 0.016.

7. CONCLUSION

Despite the degree varies, wage inequality is a widespread phenomenon for all groups, and factors related to technology such as speed, type, and skill biasedness help to determine the path of wage inequality. Since all the facets of technology cannot be captured with the available data, this thesis concentrates merely upon the skill-biased nature of technology and tries to reveal how such technological changes morph into a wage inequality accelerator. We asked what happens to wages, especially its distribution when there is a technology shock in the form of SBTC or GBT. The first and foremost obstacle of the research is the quantification of a technology shock using HLFS and then, determining a suitable technique that allows us to impose such a technology shock on the wage distribution. As a matter of fact, these two issues are solved simultaneously with the DFL semiparametric approach. According to our view, the contribution to literature, and the novelty of our study arise out of the way the data tackled with to reflect a skill-biased technical change character by virtue of counterfactual wage distributions. Attributing high skilled manufacturing workers or high technology manufacturing workers to the low scale counterparts while low skilled or low technology workers are still paid according to their own price structure is regarded as a sort of technological shock, which immediately increases their productivity. On the other hand, all low level workers cannot automatically absorb that new technology and start to a use new technique, production process, blueprint or machine, etc. Their absorptive capacity is limited to the power of decision-making, problem-solving, and creativity. Hence, we have treated education level as a fundamental determinant of how fast low skilled workers can learn new technology and start to enjoy higher wages as their productivity improve. That second procedure is also taken as a technological shift but since the education level of the low skilled workers is kept constant, it is regarded as a general purpose technology. The entire manufacturing sector experiences a new technology; however, only best-educated workers can first utilize it. In SBTC, we collectively carry low skilled workers to the high skilled attributes whereas in GPT, except education, we apply the same procedure. Therefore, for the latter case, we leave a room for their existing capability in technology adoption.

DFL counterfactual analyses give various results and to demystify those wide ranges of conclusions, we underline some important patterns. Two different technologies have different influential strengths on wage dispersions. From 2004 to 2015, SBTC had a greater inverse impact on wage inequality than the GPT and for all wage dispersion, technology shock deteriorated wage inequality. SBTC worsened the upper tail more while GPT was more detrimental to the lower tail over the period. The first case occurs because when an SBTC takes place, the upper tail, particularly, the 90th percentile or the 99th percentile can shift upward more than median and lower percentiles. High wage earners can utilize new techniques in favor of themselves and manage to increase their wage levels further. On the contrary, when there is a GPT shock, highly educated workers at the lower end of the wage distribution have the capability of absorbing new techniques and by this way, they can diverge from the ones who cannot have this ability due to lack of enough education. Therefore, lower tail wage inequality deteriorates more in the case of GPT.

On the other hand, upper tail wage dispersion was always greater than the lower tail. That is reasonable because there is a more significant downward limit of wages for the lower tail than the upper limit of wages. We can call such a situation as the “sticky floor”, a notion borrowed from the gender wage gap literature. Therefore, if a worker is at the upper tail of the wage distribution, he has more room for maneuver, in particular upward. Another result derived from the counterfactual wage distribution is one of the most striking conclusions we had but also the origination of this closely related to the previous pattern. There is a trade-off between the levels of wage and wage inequality for the period of 2004-2015. Wage levels increase due to the introduction of new technologies but also wages start to spread into a larger area, leading to higher wage inequality. This paves the way for some policy discussions. What kind of policy reform should be implemented? The goal chosen means leaving the other one on the back burner. Unless artificial refrainment is imposed on new technologies imported from abroad, in the form of heavy taxation, obsolete technologies will sooner or later be replaced by new technologies. Such replacement will end up with the deterioration of wage inequality. Therefore, there is a strong motivation to propose a policy to fill the vacuum created at the lowest part of the wage distribution rather than progressive taxation because that has been the existing practice or a revised version can be put on the agenda. Progressive taxation and wage inequality nexus is studied by Guvenen, Kuruscu and Ozkan (2014), highlighting that progressive taxation represses the wage distribution because individuals are discouraged to invest in human capital which, in turn, decreases wage inequality. On the other hand, Ales, Kurnaz and Sleet (2015) point out that high skilled workers get stuck in the highest paying jobs and that situation creates a greater area for the government to raise income taxes especially for high wage earners. They propose an optimal tax on labor with tax rises at the bottom and at the top of the wage distribution, accompanying by a moderate tax on the middle of the wage distribution. Finally, Anwar and Sun (2015) developed a three-sector general equilibrium model, and income tax was found to deteriorate skilled and unskilled wage inequality in the industry sector.

However, the trade-off between wage level and wage inequality might be only a fictional trade-off because when we look at that issue from the policy angle, governments implement policies to stimulate growth. One way to increase growth is upgrading obsolete technologies with new and more productive ones. As a by-product of better technologies, wages increase at least for those who have the capability of absorbing new technologies, machines, blueprints, etc., which is accompanied by higher wage inequality. Therefore, in this context, the immediate effect of policymakers would be higher wages, which is also seemed logical from the perspective of populist actions; henceforth, a prescription to cure wage inequality can come into sight. Yet, we should reckon among the reality of inequality but to some extent, there should be inequality, it is inevitable because theoretically everyone earns according to their contribution to the production process. Only when wage rates of equally skilled workers employed under similar conditions differentiate greatly, wage inequality might result in turmoil. Although our objective is concentrated solely on the presentation of effects of imputed technology shocks on different parts of the wage distribution; we are also aware that a panacea to overcome the trade-off is quite tough.

To shed further light on the technology identification, we also split data into low technology - high technology and conducted the same counterfactual analyses. In conclusion, both skill and technology dimensions have reasonable power to capture skill biased nature and both provide almost similar results. Nevertheless, when both cases are compared the most notable outcome is that the technology dimension is more structural and resistant against changes in wage inequality than the skill dimension. Although within year deviations of the counterfactual wage distribution from the original wage distribution were more apparent in technology case, those deviations did not pursue between years. On the other hand, within year deviations of the counterfactual wage distribution from the original wage distribution were more obscure in skill case, but that blur cleared out between years and conduced to greater wage inequality. Last but not least, when the manufacturing sector is exposed to SBTC, wage levels were higher than the case of GPT and this was valid through all years and percentiles except HS-LS analysis in 2004. Additionally, new counterfactual wage levels generated by the imposition of technology shock to low skill or low technology never exceeded high skill or high technology counterparts.

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APPENDIX A

Table A1: ISCO-08 Classification at 2-digit

1 - Managers
11 - Chief Executives, Senior Officials and Legislators
12 - Administrative and Commercial Managers
13 - Production and Specialized Services Managers
14 - Hospitality, Retail and Other Services Managers
2 - Professionals
21 - Science and Engineering Professionals
22 - Health Professionals
23 - Teaching Professionals
24 - Business and Administrative Professionals
25 - Information and Communication Technology Professionals
26 - Legal, Social and Cultural Professionals
3 - Technicians and Associated Professionals
31 - Science and Engineering Associated Professionals
32 - Teaching Associate Professionals
33 - Business and Administrative Associate Professionals
34 - Legal, Social, Cultural and related Associate Professionals
35 - Information and Communication Associate Professionals
4 - Clerical Support Workers
41 - General and Keyboard Clerks
42 - Customer Services Clerks
43 - Numerical and Material Recording Clerks
44 - Other Clerical Support Workers
5 - Services and Sales Workers
51 - Personal Services Workers
52 - Sales Workers
53 - Personal Care Workers
54 - Protective Services Workers
6 - Skilled Agricultural, Forestry and Fishery Workers
61 - Market-oriented Skilled Agricultural Workers
62 - Market-oriented Skilled Forestry, Fishery and Hunting Workers
63 - Subsistence Farmers, Fishery, Hunters and Gatherers

Sources: ILO.

Table A1: (Continued)

7 - Craft and Related Trades Workers
71 - Building and Related Trade Workers (excluding Electricians)
72 - Metal, Machinery and Related Trade Workers
73 - Handicraft and Printing Workers
74 - Electrical and Electronic Trade Workers
75 - Food Processing, Woodworking, Garment etc. Related Trade Workers
8 - Plant and Machines Operators and Assemblers
81 - Stationary Plant and Machine Operators
82 - Assemblers
83 - Drivers and Mobile Plant Operators
9 - Elementary Occupations
91 - Cleaners and Helpers
92 - Agricultural, Forestry and Fishery Laborers
93 - Laborers in Mining, construction, Manufacturing and Transport
94 - Food Preparation Assistants
95 - Street and Related Sales and Services Workers
96 - Refuse Workers and Other Elementary Workers
0 - Armed Forces Occupations
01 - Commissioned Armed Forces Officers
02 - Non-commissioned Armed Forces Officers
03 - Armed Forces Occupations, Other Ranks

Source: ILO.

Table A2: Manufacturing Industries at 2-digit (NACE Rev.2)

NACE2 Code	Section C - MANUFACTURING
10	Manufacture of food products
11	Manufacture of beverages
12	Manufacture of tobacco products
13	Manufacture of textiles
14	Manufacture of wearing apparel
15	Manufacture of leather and related products
16	Manufacture of wood and of products of wood and cork, except furniture etc.
17	Manufacture of paper and paper products
18	Printing and reproduction of recorded media
19	Manufacture of coke and refined petroleum products
20	Manufacture of chemicals and chemical products
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
22	Manufacture of rubber and plastic products
23	Manufacture of other non-metallic mineral products
24	Manufacture of basic metals
25	Manufacture of fabricated metal products, except machinery and equipment
26	Manufacture of computer, electronic and optical products
27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment n.e.c.
29	Manufacture of motor vehicles, trailers and semi-trailers
30	Manufacture of other transport equipment
31	Manufacture of furniture
32	Other manufacturing
33	Repair and installation of machinery and equipment

Source: Eurostat.

Table A3: Number of Observations: White-Blue Collar

	Low Technology				Medium Low Technology				Medium High Technology				High Technology			
year	**HSWC**	**LSWC**	**HSBC**	**LSBC**	**HSWC**	**LSWC**	**HSBC**	**LSBC**	**HSWC**	**LSWC**	**HSBC**	**LSBC**	**HSWC**	**LSWC**	**HSBC**	**LSBC**
2004	529	485	2930	2761	216	216	1072	1341	325	213	972	1047	50	30	42	62
2005	603	586	3128	3044	279	219	1315	1582	356	229	1150	1239	64	24	49	87
2006	633	600	3077	3307	341	213	1198	1706	363	248	1146	1176	65	27	30	95
2007	560	522	3063	3216	387	243	1236	1882	394	233	1112	1124	79	26	26	76
2008	686	549	2850	3204	401	274	1404	2156	467	261	1286	1327	55	28	26	78
2009	604	610	2756	3103	378	279	1357	1856	322	180	862	982	68	26	20	74
2010	750	624	3043	3507	421	276	1625	1754	430	196	968	1089	79	32	36	79
2011	763	657	3272	3570	489	274	1579	1867	533	227	926	1229	82	11	36	83
2012	667	683	3397	3428	524	303	1939	1657	555	238	1303	957	94	21	34	64
2013	696	711	3285	3459	568	345	1858	1789	558	275	1164	1048	108	19	27	73
2014	696	679	3045	3369	502	332	1781	1685	480	217	1168	902	75	24	43	58
2015	686	654	2892	3239	503	322	1706	1718	519	241	1111	976	85	25	32	75

Source: Author’s own calculations.

Table A4: Number of Observations: Aggregated Skill Level

	Low Technology		**Medium Low Technology**		**Medium High Technology**		**High Technology**	
Year	**HS**	**LS**	**HS**	**LS**	**HS**	**LS**	**HS**	**LS**
2004	3459	3246	1288	1557	1297	1260	92	92
2005	3731	3630	1594	1801	1506	1468	113	111
2006	3710	3907	1539	1919	1509	1424	95	122
2007	3623	3738	1623	2125	1506	1357	105	102
2008	3536	3753	1805	2430	1753	1588	81	106
2009	3360	3713	1735	2135	1184	1162	88	100
2010	3793	4131	2046	2030	1398	1285	115	111
2011	4035	4227	2068	2141	1459	1456	118	94
2012	4064	4111	2463	1960	1858	1195	128	85
2013	3981	4170	2426	2134	1722	1323	135	92
2014	3741	4048	2283	2017	1648	1119	118	82
2015	3578	3893	2209	2040	1630	1217	117	100

Source: Author's own calculations.

Table A5: Percentile Wages, Mean Wages, Number of Observation and Minimum Wage

LOW TECHNOLOGY

HIGH SKILLED

	Year	Mean	p10	p50	p90	N
1.47	**2004**	1.71	0.89	1.42	2.84	*3459*
1.53	**2005**	1.78	0.85	1.47	2.95	*3731*
1.52	**2006**	1.80	0.92	1.49	2.99	*3710*
1.51	**2007**	1.90	0.96	1.61	3.04	*3623*
1.63	**2008**	2.03	1.00	1.66	3.32	*3536*
1.68	**2009**	2.02	1.00	1.69	3.28	*3360*
1.69	**2010**	2.01	1.08	1.73	3.24	*3793*
1.74	**2011**	2.09	1.09	1.74	3.42	*4035*
1.79	**2012**	2.15	1.16	1.83	3.49	*4064*
1.82	**2013**	2.29	1.26	1.90	3.64	*3981*
1.84	**2014**	2.36	1.27	1.99	3.82	*3741*
1.92	**2015**	2.50	1.33	2.10	4.06	*3578*

LOW SKILLED

	Year	Mean	p10	p50	p90	N
1.47	**2004**	1.65	0.98	1.46	2.48	*3246*
1.53	**2005**	1.75	1.04	1.57	2.62	*3630*
1.52	**2006**	1.77	1.06	1.58	2.69	*3907*
1.51	**2007**	1.79	1.10	1.65	2.68	*3738*
1.63	**2008**	1.86	1.16	1.67	2.72	*3753*
1.68	**2009**	1.90	1.17	1.76	2.81	*3713*
1.69	**2010**	1.84	1.16	1.71	2.59	*4131*
1.74	**2011**	1.90	1.22	1.72	2.70	*4227*
1.79	**2012**	1.91	1.24	1.74	2.79	*4111*
1.82	**2013**	2.00	1.30	1.84	2.81	*4170*
1.84	**2014**	2.05	1.35	1.91	2.86	*4048*
1.92	**2015**	2.12	1.48	1.95	2.95	*3893*

MEDIUM LOW TECHNOLOGY

HIGH SKILLED

	Year	Mean	p10	p50	p90	N
1.47	**2004**	1.99	0.96	1.55	3.72	*1288*
1.53	**2005**	2.14	0.98	1.64	3.89	*1594*
1.52	**2006**	2.22	1.07	1.79	3.98	*1539*
1.51	**2007**	2.36	1.13	1.87	4.29	*1623*
1.63	**2008**	2.45	1.22	1.88	4.65	*1805*
1.68	**2009**	2.45	1.17	1.97	4.39	*1735*
1.69	**2010**	2.4	1.18	1.89	4.32	*2046*
1.74	**2011**	2.54	1.23	2.03	4.59	*2068*
1.79	**2012**	2.6	1.30	1.99	4.65	*2463*
1.82	**2013**	2.78	1.38	2.16	5.19	*2426*
1.84	**2014**	2.76	1.43	2.19	4.77	*2283*
1.92	**2015**	2.91	1.48	2.40	4.92	*2209*

LOW SKILLED

	Year	Mean	p10	p50	p90	N
1.47	**2004**	1.88	1.06	1.55	3.10	*1557*
1.53	**2005**	2.05	1.09	1.64	3.48	*1801*
1.52	**2006**	1.97	1.12	1.64	3.20	*1919*
1.51	**2007**	2.09	1.15	1.72	3.44	*2125*
1.63	**2008**	2.12	1.19	1.79	3.42	*2430*
1.68	**2009**	2.15	1.27	1.83	3.51	*2135*
1.69	**2010**	2.06	1.18	1.81	3.24	*2030*
1.74	**2011**	2.11	1.23	1.81	3.29	*2141*
1.79	**2012**	2.16	1.30	1.86	3.30	*1960*
1.82	**2013**	2.24	1.38	1.95	3.38	*2134*
1.84	**2014**	2.29	1.43	1.99	3.45	*2017*
1.92	**2015**	2.37	1.43	2.11	3.69	*2040*

Notes: Left-hand side of the year shows real hourly minimum wage and yellow cells indicate lower hourly real wages than hourly real minimum wage.

Source: Author's own calculations.

Table A5: (Continued)

MEDUIM HIGH TECHNOLOGY

HIGH SKILLED

	Year	Mean	p10	p50	p90	N
1.47	**2004**	2.24	1.13	1.77	3.97	*1297*
1.53	**2005**	2.35	1.15	1.87	4.10	*1506*
1.52	**2006**	2.37	1.14	1.87	4.08	*1509*
1.51	**2007**	2.51	1.24	2.08	4.40	*1506*
1.63	**2008**	2.71	1.33	2.24	4.85	*1753*
1.68	**2009**	2.84	1.41	2.34	5.27	*1184*
1.69	**2010**	2.78	1.34	2.20	4.85	*1398*
1.74	**2011**	2.94	1.35	2.28	5.53	*1459*
1.79	**2012**	2.86	1.49	2.33	4.96	*1858*
1.82	**2013**	3.1	1.56	2.54	5.41	*1722*
1.84	**2014**	3.18	1.66	2.60	5.51	*1648*
1.92	**2015**	3.39	1.77	2.77	5.91	*1630*

LOW SKILLED

	Year	Mean	p10	p50	p90	N
1.47	**2004**	2.03	1.16	1.72	3.32	*1260*
1.53	**2005**	2.18	1.23	1.84	3.69	*1468*
1.52	**2006**	2.19	1.22	1.87	3.59	*1424*
1.51	**2007**	2.13	1.24	1.85	3.44	*1357*
1.63	**2008**	2.16	1.32	1.87	3.32	*1588*
1.68	**2009**	2.31	1.43	2.03	3.51	*1162*
1.69	**2010**	2.25	1.34	2.02	3.37	*1285*
1.74	**2011**	2.32	1.32	2.03	3.67	*1456*
1.79	**2012**	2.32	1.45	2.09	3.49	*1195*
1.82	**2013**	2.42	1.50	2.16	3.59	*1323*
1.84	**2014**	2.48	1.59	2.19	3.78	*1119*
1.92	**2015**	2.54	1.64	2.30	3.69	*1217*

HIGH TECHNOLOGY

HIGH SKILLED

	Year	Mean	p10	p50	p90	N
1.47	**2004**	3.09	1.18	2.60	6.14	*92*
1.53	**2005**	2.99	1.15	2.05	6.55	*113*
1.52	**2006**	3.43	1.42	2.80	6.73	*95*
1.51	**2007**	4.07	1.37	3.30	8.25	*105*
1.63	**2008**	4.56	1.32	3.73	8.71	*81*
1.68	**2009**	5.13	2.04	4.68	8.78	*88*
1.69	**2010**	4.2	1.62	3.45	8.09	*115*
1.74	**2011**	4.06	1.65	3.41	8.51	*118*
1.79	**2012**	4.48	2.01	3.72	8.68	*128*
1.82	**2013**	5.23	1.96	4.73	9.23	*135*
1.84	**2014**	4.57	1.72	3.58	9.07	*118*
1.92	**2015**	4.86	1.91	3.99	9.85	*117*

LOW SKILLED

	Year	Mean	p10	p50	p90	N
1.47	**2004**	2.02	1.06	1.70	3.54	*92*
1.53	**2005**	2.14	1.27	1.84	3.51	*111*
1.52	**2006**	2.46	1.36	2.15	4.11	*122*
1.51	**2007**	2.18	1.22	1.87	3.44	*102*
1.63	**2008**	2.64	1.35	2.18	4.98	*106*
1.68	**2009**	2.72	1.41	2.34	4.27	*100*
1.69	**2010**	2.71	1.39	2.10	5.18	*111*
1.74	**2011**	2.5	1.39	2.08	4.42	*94*
1.79	**2012**	2.76	1.51	2.23	4.71	*85*
1.82	**2013**	2.51	1.45	2.00	4.33	*92*
1.84	**2014**	2.54	1.53	2.10	3.82	*82*
1.92	**2015**	2.48	1.57	2.22	3.93	*100*

Notes: Left-hand side of the year shows real hourly minimum wage and yellow cells indicate lower hourly real wages than hourly real minimum wage.

Source: Author's own calculations.

Table A6: Actual and Counterfactual Wages in Levels

Time and Skill/Technology	Wages at Specific Percentiles							Wage Differentials				
HS-LS 2004	**p99**	**p90**	**p75**	**p50**	**p25**	**p10**	**p01**	**p90-p10**	**p90-p50**	**p50-p10**	**p75-p25**	**p99-p01**
LS with HS (SBTC_LS)	1.732	1.026	0.712	0.429	0.209	-0.026	-0.560	1.052	0.597	0.455	0.502	2.292
LS	1.622	1.010	0.712	0.445	0.225	0.005	-0.513	1.005	0.565	0.440	0.487	2.135
LS without NACE	1.622	0.994	0.696	0.429	0.225	0.005	-0.482	0.989	0.565	0.424	0.471	2.104
LS without Education (GPT_LS)	1.685	1.041	0.727	0.445	0.241	0.021	-0.513	1.020	0.597	0.424	0.487	2.198
HS	1.920	1.183	0.790	0.429	0.162	-0.089	-0.670	1.272	0.754	0.518	0.628	2.590
HS-LS 2015	**p99**	**p90**	**p75**	**p50**	**p25**	**p10**	**p1**	**p90-p10**	**p90-p50**	**p50-p10**	**p75-p25**	**p99-p01**
LS with HS (SBTC_LS)	1.868	1.291	1.010	0.759	0.552	0.359	-0.129	0.932	0.532	0.399	0.458	1.996
LS	1.735	1.173	0.951	0.714	0.537	0.359	-0.070	0.813	0.458	0.355	0.414	1.804
LS without NACE	1.764	1.202	0.966	0.729	0.552	0.359	-0.129	0.843	0.473	0.370	0.414	1.893
LS without Education (GPT_LS)	1.823	1.232	0.966	0.729	0.552	0.359	-0.070	0.872	0.503	0.370	0.414	1.893
HS	2.356	1.587	1.173	0.847	0.581	0.359	-0.114	1.227	0.739	0.488	0.592	2.470
LT-HT 2004	**p99**	**p90**	**p75**	**p50**	**p25**	**p10**	**p1**	**p90-p10**	**p90-p50**	**p50-p10**	**p75-p25**	**p99-p01**
LT with HT (SBTC_LT)	1.936	1.230	0.821	0.476	0.241	0.021	-0.450	1.209	0.754	0.455	0.581	2.386
LT	1.732	1.010	0.696	0.398	0.162	-0.073	-0.607	1.083	0.612	0.471	0.534	2.339
LT without Occupation	1.732	1.010	0.696	0.398	0.162	-0.073	-0.623	1.083	0.612	0.471	0.534	2.355
LT without Education (GPT_LT)	1.779	1.041	0.712	0.413	0.178	-0.058	-0.591	1.099	0.628	0.471	0.534	2.371
HT	1.983	1.308	0.916	0.570	0.319	0.115	-0.513	1.193	0.738	0.455	0.597	2.496
LT-HT 2015	**p99**	**p90**	**p75**	**p50**	**p25**	**p10**	**p1**	**p90-p10**	**p90-p50**	**p50-p10**	**p75-p25**	**p99-p01**
LT with HT (SBTC_LT)	2.252	1.557	1.158	0.847	0.611	0.433	0.064	1.124	0.710	0.414	0.547	2.189
LT	2.060	1.306	1.010	0.729	0.537	0.330	-0.114	0.976	0.577	0.399	0.473	2.174
LT without Occupation	2.104	1.335	1.025	0.744	0.537	0.330	-0.114	1.006	0.592	0.414	0.488	2.218
LT without Education (GPT_LT)	2.089	1.335	1.025	0.744	0.537	0.345	-0.129	0.991	0.592	0.399	0.488	2.218
HT	2.430	1.675	1.247	0.936	0.685	0.522	0.152	1.153	0.739	0.414	0.562	2.277

Source: Author’s own calculations.

Table A6: (Continued)

Time and Skill/Technology	Wages at Specific Percentiles							Wage Differentials				
2015-2004	**p99**	**p90**	**p75**	**p50**	**p25**	**p10**	**p1**	**p90-p10**	**p90-p50**	**p50-p10**	**p75-p25**	**p99-p01**
2015 with 2004	2.048	1.281	1.002	0.723	0.496	0.269	-0.201	1.011	0.558	0.453	0.506	2.249
2015	2.205	1.385	1.054	0.775	0.566	0.357	-0.097	1.029	0.610	0.418	0.488	2.301
2015 without Education	2.117	1.333	1.037	0.758	0.548	0.357	-0.079	0.976	0.575	0.401	0.488	2.197
2004	1.821	1.089	0.740	0.426	0.200	-0.044	-0.602	1.133	0.662	0.471	0.540	2.423

Source: Author's own calculations.

APPENDIX B

Table B1: Probit Estimation for Weighting Function: Skill Dimension

	(2004)			(2015)		
Variables	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Experience	0.0123	0.0126	0.00694	-0.0121	0.0276*	0.00235
	(0.0155)	(0.0154)	(0.0150)	(0.0137)	(0.0146)	(0.0132)
Experience^2	2.91e-05	0.000552	7.09e-05	0.000193	1.10e-05	-6.51e-05
	(0.000348)	(0.000343)	(0.000336)	(0.000242)	(0.000290)	(0.000242)
Marital Status	-0.0824*	-0.0583	-0.0585	-0.121***	-0.107***	-0.104***
	(0.0427)	(0.0422)	(0.0415)	(0.0370)	(0.0367)	(0.0357)
Social Security	0.157***	0.121***	0.147***	0.186***	0.124***	0.0754*
	(0.0369)	(0.0365)	(0.0355)	(0.0462)	(0.0457)	(0.0448)
Tenure	-0.0218***	-0.0213***	-0.0241***	-0.0146***	-0.0171***	-0.0156***
	(0.00284)	(0.00283)	(0.00272)	(0.00227)	(0.00234)	(0.00220)
Firm Size_50+	0.290***	0.252***	0.425***	0.265***	0.209***	0.340***
	(0.0306)	(0.0300)	(0.0283)	(0.0277)	(0.0271)	(0.0257)
Age Cohorts						
Age(25_29)	0.0443	-0.125**	0.0518	0.110	-0.223***	0.0750
	(0.0602)	(0.0575)	(0.0583)	(0.0676)	(0.0642)	(0.0652)
Age(35_39)	-0.00775	-0.366***	-0.00343	0.115	-0.377***	0.0679
	(0.0982)	(0.0905)	(0.0957)	(0.0944)	(0.0916)	(0.0917)
Age(40_44)	-0.0909	-0.605***	-0.0865	0.147	-0.449***	0.0731
	(0.132)	(0.119)	(0.129)	(0.108)	(0.112)	(0.107)
Age(45_49)	-0.142	-0.852***	-0.118	0.0906	-0.616***	0.0348
	(0.182)	(0.164)	(0.177)	(0.125)	(0.140)	(0.127)
Age(50_54)	-0.148	-1.120***	-0.122	0.106	-0.722***	0.0438
	(0.259)	(0.237)	(0.251)	(0.152)	(0.182)	(0.158)
Age(55_59)	-0.260	-1.476***	-0.203	0.123	-0.833***	0.0975
	(0.347)	(0.321)	(0.335)	(0.194)	(0.245)	(0.205)

Age(60_64)	-0.553	-1.978***	-0.450	0.308	-0.729**	0.487*
	(0.493)	(0.465)	(0.479)	(0.279)	(0.343)	(0.292)
Education						
Primary School	-0.0353		-0.0209	-0.0893**		-0.144***
	(0.0386)		(0.0378)	(0.0371)		(0.0363)
High School	0.0328		0.0333	-0.0538		-0.0763
	(0.0468)		(0.0449)	(0.0490)		(0.0466)
Vocational High School	-0.175***		-0.219***	-0.305***		-0.410***
	(0.0464)		(0.0438)	(0.0415)		(0.0401)
College	-0.990***		-0.996***	-0.889***		-0.950***
	(0.0731)		(0.0693)	(0.0503)		(0.0483)
Industry						
Nace_11	0.417***	0.403***		0.788***	0.750***	
	(0.154)	(0.151)		(0.167)	(0.171)	
Nace_12	0.303	0.288		-0.282	-0.452	
	(0.309)	(0.300)		(0.316)	(0.319)	
Nace_13	0.504***	0.520***		0.276***	0.310***	
	(0.0560)	(0.0554)		(0.0497)	(0.0490)	
Nace_14	0.522***	0.553***		0.434***	0.497***	
	(0.0518)	(0.0515)		(0.0526)	(0.0518)	
Nace_15	-0.248***	-0.226***		-0.250***	-0.183**	
	(0.0841)	(0.0838)		(0.0835)	(0.0826)	
Nace_16	-0.151*	-0.135*		-0.253***	-0.254***	
	(0.0804)	(0.0802)		(0.0857)	(0.0836)	
Nace_17	0.932***	0.910***		0.144	0.133	
	(0.125)	(0.126)		(0.0981)	(0.0965)	
Nace_18	-0.261***	-0.255***		-0.854***	-0.894***	
	(0.0980)	(0.0976)		(0.117)	(0.112)	
Nace_19	0.769***	0.747***		0.158	-0.00500	
	(0.285)	(0.289)		(0.218)	(0.224)	
Nace_20	0.383***	0.388***		0.427***	0.313***	
	(0.0684)	(0.0676)		(0.0829)	(0.0868)	

Nace_21	0.563***	0.275		0.313**	0.101	
	(0.166)	(0.175)		(0.155)	(0.169)	
Nace_22	0.949***	0.947***		0.651***	0.654***	
	(0.0770)	(0.0764)		(0.0688)	(0.0680)	
Nace_23	0.233***	0.237***		0.156***	0.148***	
	(0.0632)	(0.0626)		(0.0530)	(0.0522)	
Nace_24	0.133*	0.124*		-0.217***	-0.232***	
	(0.0718)	(0.0715)		(0.0585)	(0.0576)	
Nace_25	0.0792	0.0909		-0.645***	-0.615***	
	(0.0643)	(0.0638)		(0.0590)	(0.0585)	
Nace_26	0.0546	0.0161		-0.375***	-0.522***	
	(0.141)	(0.142)		(0.123)	(0.126)	
Nace_27	0.283***	0.265***		-0.133*	-0.155**	
	(0.0813)	(0.0800)		(0.0696)	(0.0680)	
Nace_28	-0.157**	-0.200***		-0.375***	-0.412***	
	(0.0743)	(0.0733)		(0.0624)	(0.0613)	
Nace_29	0.201***	0.157***		-0.216***	-0.261***	
	(0.0620)	(0.0608)		(0.0576)	(0.0569)	
Nace_30	-0.602***	-0.588***		-0.730***	-0.743***	
	(0.160)	(0.158)		(0.135)	(0.134)	
Nace_31	-0.879***	-0.856***		-0.849***	-0.798***	
	(0.0804)	(0.0796)		(0.0609)	(0.0594)	
Nace_32	-0.151	-0.125		-0.327***	-0.333***	
	(0.115)	(0.114)		(0.107)	(0.108)	
Nace_33	-0.160	-0.0961		-1.247***	-1.317***	
	(0.299)	(0.306)		(0.117)	(0.114)	
Constant	-0.515***	-0.650***	-0.283**	0.155	-0.419***	0.0447
	(0.153)	(0.149)	(0.144)	(0.144)	(0.142)	(0.134)
Pseudo R2	0.1048	0.0889	0.0433	0.1225	0.0990	0.0435
Observations	12,264	12,264	12,264	14,784	14,784	14,784

Notes: The omitted category for dummies; having no schooling for education, 15–19 years for age interval, less than 10 workers for firm size, unmarried for marital status, agricultural sector for industry, executive manager for occupation. Sample weights are used and robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: Author’s own calculations.

Table B2: Probit Estimation for Weighting Function: Technology Dimension

	(2004)			(2015)		
Variables	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Experience	0.0198	0.0326*	0.0202	0.0199	0.0417***	0.0175
	(0.0170)	(0.0169)	(0.0169)	(0.0147)	(0.0153)	(0.0147)
Experience^2	-0.000585	-0.000114	-0.000583	-0.000534**	-0.000471	-0.000495*
	(0.000381)	(0.000379)	(0.000380)	(0.000261)	(0.000294)	(0.000259)
Marital Status	0.0241	0.0123	0.0215	0.0580	0.0424	0.0584
	(0.0449)	(0.0448)	(0.0448)	(0.0402)	(0.0401)	(0.0400)
Social Security	-0.366***	-0.424***	-0.364***	-0.565***	-0.619***	-0.567***
	(0.0439)	(0.0435)	(0.0438)	(0.0642)	(0.0645)	(0.0642)
Tenure	-0.00404	-0.00455	-0.00417	-0.00437*	-0.00844***	-0.00576**
	(0.00302)	(0.00302)	(0.00300)	(0.00253)	(0.00247)	(0.00251)
Firm Size_50+	-0.307***	-0.367***	-0.300***	-0.385***	-0.437***	-0.377***
	(0.0322)	(0.0316)	(0.0315)	(0.0298)	(0.0294)	(0.0292)
Age Cohorts						
Age(25_29)	-0.0616	-0.257***	-0.0611	-0.0567	-0.237***	-0.0568
	(0.0639)	(0.0616)	(0.0638)	(0.0728)	(0.0701)	(0.0725)
Age(35_39)	-0.0107	-0.444***	-0.0141	0.0464	-0.261***	0.0441
	(0.105)	(0.0977)	(0.105)	(0.102)	(0.0987)	(0.102)
Age(40_44)	0.147	-0.488***	0.140	0.144	-0.261**	0.139
	(0.141)	(0.130)	(0.141)	(0.118)	(0.116)	(0.117)
Age(45_49)	0.125	-0.732***	0.114	0.153	-0.359**	0.144
	(0.196)	(0.180)	(0.196)	(0.135)	(0.140)	(0.133)
Age(50_54)	0.390	-0.743***	0.373	0.452***	-0.188	0.434***
	(0.285)	(0.266)	(0.285)	(0.168)	(0.181)	(0.166)
Age(55_59)	0.455	-0.960***	0.431	0.338	-0.414*	0.306
	(0.372)	(0.351)	(0.372)	(0.218)	(0.245)	(0.216)
Age(60_64)	0.580	-1.136**	0.553	0.820***	-0.0924	0.812***
	(0.551)	(0.530)	(0.550)	(0.307)	(0.343)	(0.305)
Occupation						

Professionals	-0.104	-0.211		-0.108	-0.0849	
	(0.148)	(0.146)		(0.106)	(0.107)	
Technicians & Associate Pro.	-0.104	-0.00466		-0.00893	0.0329	
	(0.122)	(0.117)		(0.0918)	(0.0895)	
Clerical Support Workers	0.0981	0.211*		0.120	0.204**	
	(0.128)	(0.123)		(0.0992)	(0.0974)	
Services & Sales Workers	-0.0657	0.171		0.271**	0.403***	
	(0.135)	(0.128)		(0.113)	(0.110)	
Skilled Agri., Fore. & Fish. W.	0.451	0.728		0.600	0.586	
	(0.549)	(0.534)		(0.498)	(0.571)	
Craft & Related Trades W.	-0.0487	0.178*		0.186**	0.330***	
	(0.116)	(0.107)		(0.0867)	(0.0813)	
Plant & Machine Ope. & Asse.	0.0312	0.269**		0.330***	0.503***	
	(0.116)	(0.107)		(0.0888)	(0.0829)	
Elementary Occupations	-0.0533	0.214*		0.231**	0.411***	
	(0.123)	(0.115)		(0.0918)	(0.0859)	
Education						
Primary School	-0.0348		-0.0337	-0.104**		-0.124***
	(0.0432)		(0.0431)	(0.0436)		(0.0432)
High School	-0.203***		-0.199***	-0.116**		-0.150***
	(0.0499)		(0.0490)	(0.0541)		(0.0539)
Vocational High School	-0.497***		-0.496***	-0.526***		-0.577***
	(0.0470)		(0.0463)	(0.0446)		(0.0436)
College	-0.640***		-0.667***	-0.391***		-0.582***
	(0.0792)		(0.0678)	(0.0590)		(0.0505)
Constant	1.287***	0.728***	1.257***	1.394***	0.834***	1.674***
	(0.206)	(0.193)	(0.162)	(0.178)	(0.169)	(0.151)
Pseudo R2	0.0620	0.0487	0.0607	0.0789	0.0656	0.0745
Observations	12,264	12,264	12,264	14,784	14,784	14,784

Notes: The omitted category for dummies; having no schooling for education, 15–19 years for age interval, less than 10 workers for firm size, unmarried for marital status, agricultural sector for industry, executive manager for occupation. Sample weights are used and robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: Author's own calculations.