AN INVESTIGATION OF INCOME PROFILES IN TURKEY

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BOĞAZİÇİ UNIVERSITY

2017

AN INVESTIGATION OF INCOME PROFILES IN TURKEY

Thesis submitted to the
Institute for Graduate Studies in Social Sciences
in partial fulfillment of the requirements for the degree of

Master of Arts
in
Economics

by
Emrehan Aktuğ

Boğaziçi University
2017

An Investigation of Income Profiles in Turkey

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DECLARATION OF ORIGINALITY

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ABSTRACT

An Investigation of Income Profiles in Turkey

In this paper, I empirically investigate the labor income profiles in Turkey over age, gender, educational attainment and public-private sector employment. I first document that the average labor income profile over age is quite flat yet non-decreasing in Turkey, contrary to the observed hump-shaped profile in developed countries. This pattern is the result of aggregation, as there is a considerable degree of heterogeneity in income profiles over the highlighted characteristics. I show that the private sector income profiles display a higher degree of cross-sectional variation across individuals over the same age groups, especially among university graduates. Having established the results, I turn to verifying my predictions employing both OLS with different datasets and a pseudo-panel estimation approach via the synthetic cohorts I generate. My econometric findings provide robustness and verify the validity of the significance of my findings.

ÖZET

Türkiye'deki İş Geliri Profilleri

Bu çalışmada Türkiye'deki işçi geliri profillerini yaş, cinsiyet, eğitim durumu ve kamu-özel sektör değişkenlerini kullanarak analiz ettim. İlk olarak, gelişmiş ülkelerde gözlenen kambur biçimindeki maaş profilinin aksine Türkiye'deki ortalama maaş profilinin özellikle 40 yaşından sonra yaklaşık olarak sabit kaldığını buldum. Fakat bahsedilen değişkenlerin gelir profilleri üzerinde önemli ölçüde değişikliklere sebep olması veriyi gruplara ayırdığımda çok farklı profiller elde etmemi sağlıyor. Yüksek eğitim ve gelir gruplarında, kambur biçimindeki profil yerini doğrusal artan bir profile bırakıyor. Aynı zamanda özel sektörde çalışan üniversite mezunları kamuda çalışanlara göre ortalamada daha çok kazanmalarına rağmen işçi geliri varyansının özel sektörde çok daha yüksek olduğu görülebiliyor. Veriden elde ettiğim bulgular Türkiye'de hem eğitim hem sektör etkisiyle maaşların hayat döngüsü içerisinde çok farklı rotalar seyrettiğini gösteriyor. Bu elde ettiğim sonuçları hem basit doğrusal regresyon analizi hem de yapay panel veri oluşturma yöntemi ile test ettim ve ekonometrik bulgularım veride gördüklerimi doğruladı.

ACKNOWLEDGMENTS

This thesis study is a result of a long process to which many people contributed. First of all, I would like to thank the members of my thesis committee, Assist. Prof. Orhan Torul, Assist. Prof. Tolga Umut Kuzubaş, and Assoc. Prof. Türkmen Göksel for their valuable time for spending their valuable time reading this work.

I am particularly indebted to my thesis supervisor, Assist. Prof. Orhan Torul, who accepted the supervision of this thesis and who was very helpful while I was writing it. I would not have finished it without his support.

I would like to express my sincere gratitude to Assist. Prof. Tolga Umutu Kuzubaş and Assoc. Prof. Murat Kırdar. I always had the chance to show my findings to them and get their comments, which kept me on track.

I would like to express my deepest gratitude to TÜBİTAK BİDEB which supported me both academically and financially throughout my graduate education.

All of the work done during the preparation of this thesis would not have been possible without the support of my family. My parents, Gülten and Mustafa Aktuğ, were always with me. I would like to thank my family for their love and support throughout my whole life.

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CHAPTER 1

INTRODUCTION

The income and wealth inequality in the world is becoming more visible in recent decades. Much of the rise in inequality has reflected a widening dispersion of labor income. Turkey is not an exception and has the fourth highest level of income inequality and poverty among OECD countries.[1] To investigate the determinants of labor income inequality in Turkey, I look at the labor income profiles over the life cycles of Turkish residents.

The literature which examines income and consumption profiles over life cycle has expanded in recent years, particularly for developed countries. Given the lack of long period panel data in Turkey, I use a large cross-sectional data set for the analysis of labor income profiles over the life cycles of different groups based on gender, educational attainment and private-public sector employment. The wide range of data allows me to study the impact of characteristics of individuals on labor income over life cycle. I have found a quite flat life cycle income profile for the whole sample, but the shape varies significantly, depending on educational attainment and public-private sector employment. There is an increasing profile for university graduates, whereas for the workers who have primary or lower education, the labor income profile is hump-shaped. I observe an increasing income profile in the public sector over each education cluster, but the profile is hump-shaped in the private sector. This paper proposes that there is a significant risk-return trade-off in the public-private sector employment choice of Turkish residents, recognizing the existence of a gender pay gap in Turkey, that is more noticeable in the private than in the public sector.

[1] There are 35 member countries.

In the estimation part of the research, I use the Ordinary Least Square (OLS) method to check the statistical significance of effects that I have seen in the descriptive part. In fact, OLS results indicate that the life cycle labor income profile is clearly hump-shaped over age, with a peak at age 40-44. I did the same analysis using two different datasets and got similar results. In addition, using a pseudo-panel approach, I created artificial cohorts based on time-invariant characteristics.[2] Then, I compare the estimation results for different cohort formations and data specifications. The main contribution of the paper is the estimation of labor income profiles using different techniques, which allows me to investigate the impacts of educational attainment, gender and public-private sector employment on labor income in Turkey, thanks to the characteristics being defined at cohort level.

The longitudinal analysis in the absence of genuine panel data provides information on the labor income level of various groups in Turkey as well as structural characteristics such as an education premium, volatility gap between sectors, and gender pay gap. The rest of paper is organized as follows: Chapter 2 summarizes the previous literature on labor income profiles in Turkey. Chapter 3 describes the data and provides a detailed description of the labor income of various clusters. Chapter 4 explains the methodology. Chapter 5 presents the estimation results using both OLS and the pseudo-panel approach. Chapter 6 concludes.

[2]Considering the trade-off between cohort size and number of cohorts, I use different specifications for cohort formation.

CHAPTER 2

LITERATURE REVIEW

The average labor income profile exhibits a hump-shaped pattern in developed countries, as is known from the literature (Attanasio, 1995; Alessie, 1997). In Turkey, Cilasun and Kirdar (2009) investigate the life cycle aggregate income profiles of household heads by educational attainment for the year 2003, and they find out that aggregate income profiles conditional on educational attainment are non-decreasing and quite flat over life cycle. Nevertheless, the labor income life cycle profile of the whole population is hump-shaped with a peak at age 40-44. For university graduates, the peak occurs earlier.[3]

Household Budget Survey (HBS) data is widely used for other types of analysis, including income inequality, precautionary saving, income and expenditure decompositions. Nazli (2014) looks at the aged-based consumption profile and its components over life cycle by examining only 2006 data and focuses mainly on savings decisions of households. Income and saving profiles are investigated by Yukseler and Turkan (2008) for the 2002-2005 period with a descriptive perspective; they find negative saving rates for the first and second quintiles. A precautionary saving analysis is conducted by Ceritoglu (2009) with the underlying motive of uncertainty in labor income by considering only the households with positive saving rates. Eksi and Kirdar (2015) investigate wage inequality in Turkey for the 2002-2011 period. Labor income based on educational attainment is a part of the analysis, but without any econometric model or panel analysis.

[3] The peak of life cycle labor income profile of university graduates occurs at age 35-39.

To my knowledge, only Cilasun (2009) forms pseudo-panel data to obtain different cohorts based on educational attainment for household heads using 2002-2005 data.[4] There is no further specification for the cohorts beyond the birth years. Thus, there is no possible econometric analysis to investigate the effect of educational attainment, gender, and public-private sector employment. He provides a descriptive analysis and can only support it with the cohort and year effects because of a lack of time-invariant characteristics in the definition of cohorts, which I am able to incorporate into my paper thanks to a wider data set.

The contribution of this study is the estimation of the effects of education, gender and public-private sector employment on labor income by forming cohorts both with OLS and with a method that differs from what was used in previous research. Rather than creating groups by birth year with a 1-year span, I use a 5-year span.[5] For instance, the 1950-1954 generation will be followed over 2002-2014 by further separating them according to their educational attainment, gender, and public-private sector employment.

[4] Since he uses 2002-2005 data, the cohorts can be followed over 4 years, which are formed according to the date of birth. For example, individuals aged 25 in 2002, aged 26 in 2003, aged 27 in 2003 and aged 28 in 2005 together form one cohort. Since only the household heads aged 25-70 are taken into account, 43 cohorts are formed that correspond to a total observation of 172, due to being balanced panel data.

[5] With a 5-year span, cohort sizes are larger, so the measurement error is lower.

CHAPTER 3

DATA AND DESCRIPTIVE STATISTICS

3.1 Data

I use cross-sectional data from the Turkish Household Budget Survey (HBS) covering the period 2002-2014. It is conducted every year by the Turkish Statistical Institute (TUIK) on a representative sample of about 10,000 Turkish households.

Income indicates the total labor income in a year, consisting of cash, income received in kind and premiums. Income data are adjusted to 2014 and a lower limit for every year is established based on the respective minimum wage, so that part-time workers, the ones who work only at some months of the year and the unemployed are excluded from the descriptive analysis. The data includes eleven different education values, which I reduce to three levels by categorizing individuals with 1 to 8 years of education as primary school graduates, 9 to 12 years of education as high school graduates and the remaining ones who completed bachelor's degree or higher as university graduates. Although these categories are available in the data for the whole range, information for the public-private sector was recorded only for 2002-2011 range, which leads to corresponding estimation results obtained with fewer observations. Employees in the state-owned enterprises (SOEs) are considered public sector employees due to the small number of observations and characteristics of SOEs that are similar to those of the public sector in Turkey (Tansel, 2004).

HBS includes socioeconomic characteristics of individuals so that clustering based on gender, educational attainment and public-private sector employment is possible. The sample sizes for each year are similar, but the composition changes slightly so that aggregation is not implausible. For example, the ratio of university graduates over the general population increases over the years. Even so, I have made the age-period-cohort analysis in Appendix B to avoid potential problems coming from clustering each age group from different years. Lastly, I group ages in 5-year intervals instead of 1-year intervals to get a sufficient number of observations in each cell so that further decomposition for various clustering setups are possible.

3.2 Descriptive statistics

I first report the graphical analysis of the household income profiles over life cycle with various clusters. I use box plots as graphics to show the median and the first and third quartiles. On the box plot, the end of the whiskers represents the lowest observation within 1.5 times the interquartile range of the lower quartile and the highest observation within 1.5 times the interquartile range of the upper quartile (Tukey, 1997). The distributional appearance is more informative than the mere mean income of individuals.

For the life cycle analysis, the ideal way is to follow individuals over a long time period, for which panel data is necessary. I cluster the cross-sectional data based on gender, educational attainment and public-private sector employment. Thus, there is a sufficient number of observations for each cluster to demonstrate the labor income distribution of each age group. Mainly, I expect to observe that the secular time trends cause changes in the shape of life cycle income profiles. That is why I conduct a life cycle analysis conditional on various variables.[6]

[6] Since there are very few observations after age 60, these extreme observations are excluded, except in Figure 1.

3.2.1 Labor income

Figure 1 plots the distribution of labor income against the age groups created with 5-year periods. The labor income increases until age 45, after which point the median starts to decline and the variance increases. Labor income over life cycle is not exactly hump-shaped; it is rather quite flat, especially between age 35 and 55. The peak of mean labor income is at age 55-59, which is too late compared to the result of previous studies (Cilasun and Kirdar, 2009). The reason is that I consider only full-time employees here, whereas they take into account all positive labor income earners.[7] Another crucial point is that, when I control for year effects in OLS part, the hump-shaped pattern over age groups can be clearly observed (see Chapter 5).

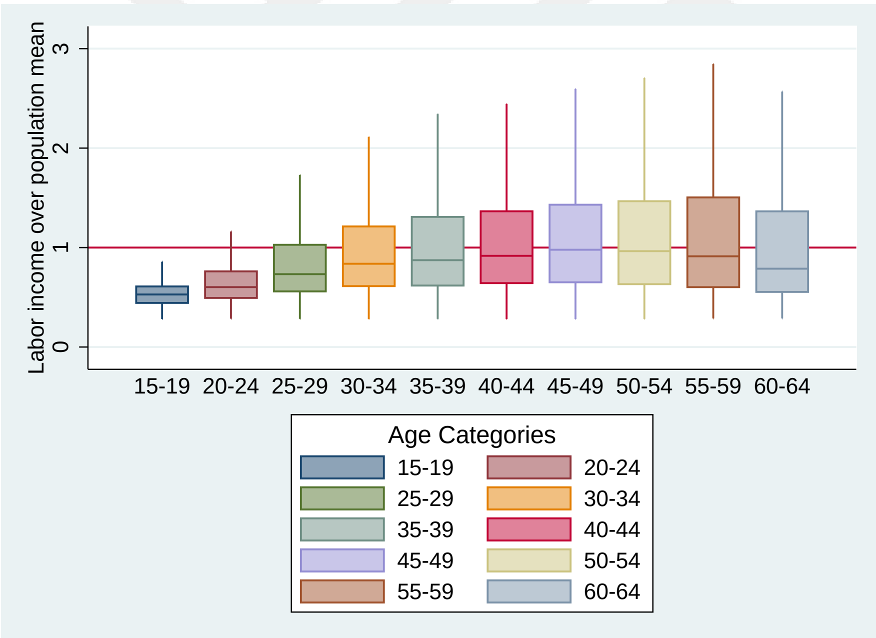


Figure 1. Labor income distribution

In addition, the cause of the sharp decrease after age 60 is the effect of retirement.[8] Although the labor income decreases after that point, the aggregate income in Turkey increases (Cilasun and Kirdar, 2013), so people do not need to work in retirement.

[7] I follow the OECD (2012) for this approach.
[8] The retirement age in Turkey (since 1999) is 60.

Only the ones who are in poor financial situation tend to work after retirement, which is the main reason for the decline. In addition, the number of observations is relatively low for both the 15-19 and 60-64 age groups. Thus, I restrict my analysis to the sample to the 20-59 age group.

3.2.2 Education

Educational attainment is one of the determining factors for wage differences within age categories. As shown in Figure 2, labor income increases with the level of schooling. For university graduates, the expected income increases sharply between age 25 and 34, while after age 35, the distribution nearly stays same; there is no increase, with the exception of the 55-59 age category. For most of those who have primary or lower education, the labor income is below the mean of the sample. The median stays the same after age 30. Only the variance is hump-shaped, with the peak at age 45-49. For high school graduates, there is an increase until age 50-54, and the median of each age category is around the sample mean.

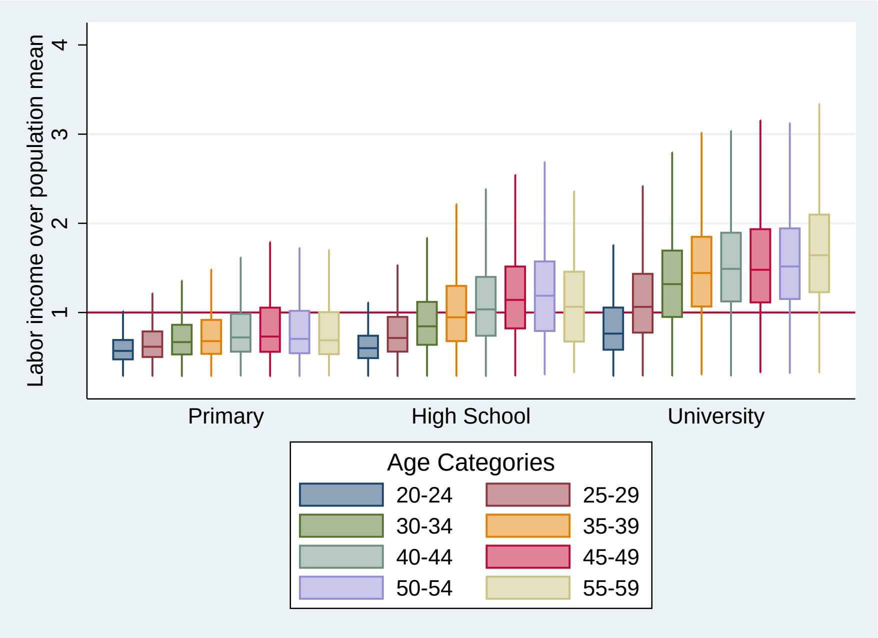


Figure 2. Labor income distribution based on education

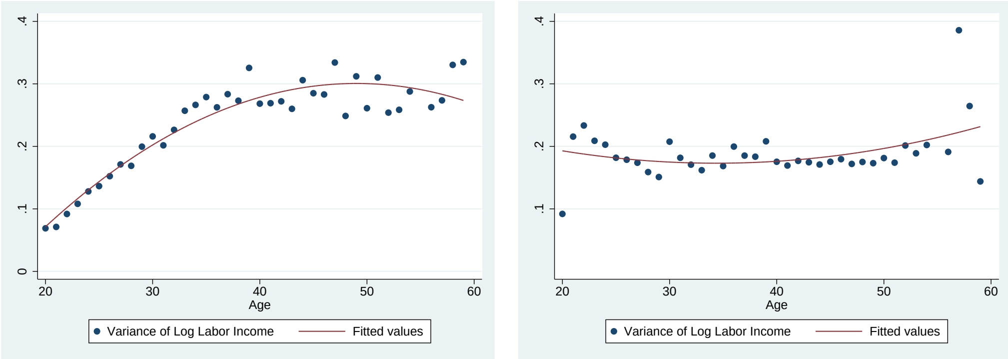
Since those who have primary or high school education are generally employed in low paying jobs that do not require high mental skills, the physical condition is what determines productivity. The learning process is slow, productivity increases until the 50s, but after age 50 the physical capabilities deteriorate and the income level decreases with decreasing productivity. For university graduates, the learning process is fast, and between age 25 and 35 they get the necessary skills for a job. After that, productivity does not increase significantly. Due to less dependence on the physical condition, labor income may even increase at age 55 as individuals approach retirement.

3.2.3 Sector

Figure 3 plots the income distribution conditional on the sector. For those employed in the public sector, the income profile over life cycle increases monotonically. The reason is that, in the public sector, what an individual earns is already determined by the state. And with increasing age and promotions, the labor income increases steadily. The positive trend in the public sector is also correlated with educational attainment, because half of those employed in the public sector are already university graduates, whereas in the private sector only 13% are.

Figure 3. Labor income distribution based on sector

I expect to observe higher wage rates for the private sector. On the contrary, there is a significant pay gap between public-private sector in favor of the public sector. The income profile is hump-shaped in the private sector, and the income level is lower than in the public sector for every age group. In addition, Figure 4 demonstrates that the variance of income is higher in the private sector after age 30 and it follows a hump-shaped profile, whereas it is nearly constant in the public sector for all ages. In section 3.2.4, further specification based on educational attainment within the sector will provide necessary information on the pay gap between sectors and for the variance difference as well.



(a) Private sector (b) Public sector

Figure 4. Variance of log labor income

3.2.4 Combining education and sector

There is a significant difference between education groups in the private sector, unlike in the public sector. Nearly all of those, who have primary or lower education earn less than the mean labor income of the general population, whereas university graduates have the highest mean and median income in the population. The volatility of income for university graduates is higher in the private than in the public sector. For each education group in the public sector, there is an increasing labor income profile which is consistent with the explanation above about promotions. However, in the private sector, the peak income in the profile is at age 40-44, after which point the median income decreases.

Figure 5 demonstrates that, for the public sector, a positive trend at a moderate level exists for each educational attainment, and the income difference is low compared to private sector. For those who are employed in the private sector, the income difference between groups is striking. The reason is that the private sector in Turkey employs mostly low-qualified or low-skilled workers, at the minimum wage. Figure 6 shows that the labor income distribution is left skewed in the private sector; a large share of workers in the private sector earn around the minimum wage. The step-wise increase in labor income until about 10,000 TL/year is due to the increasing minimum wage over the years.

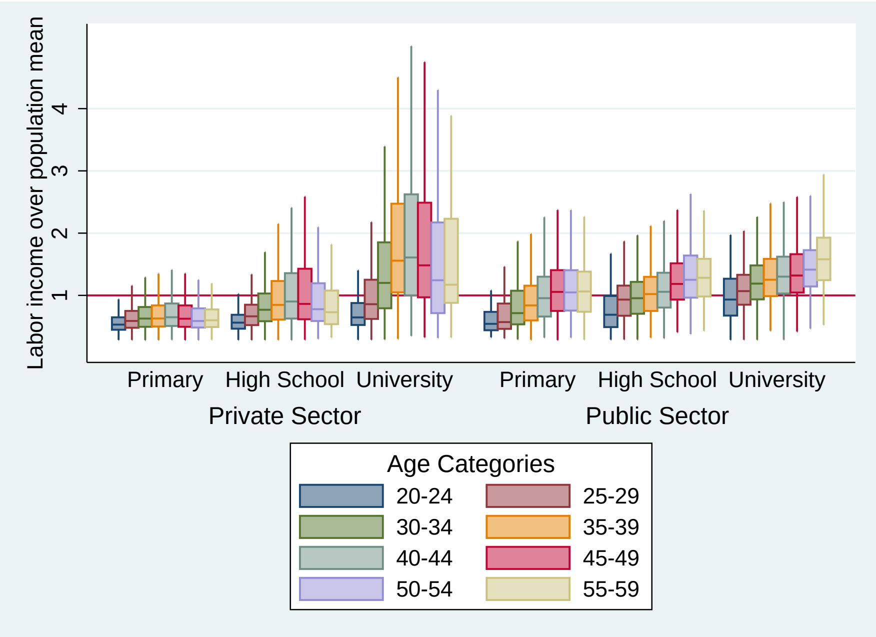


Figure 5. Labor income distribution based on education-sector clusters

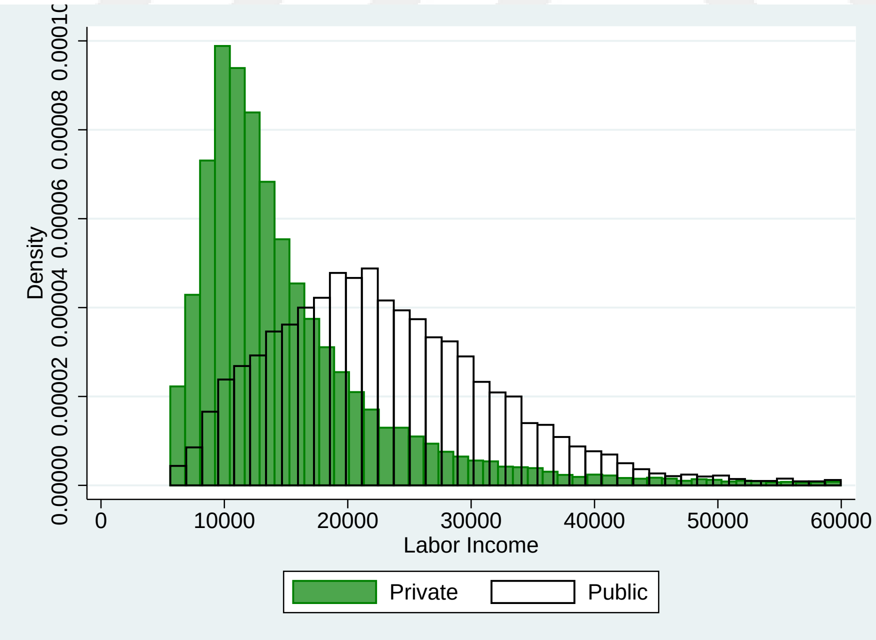
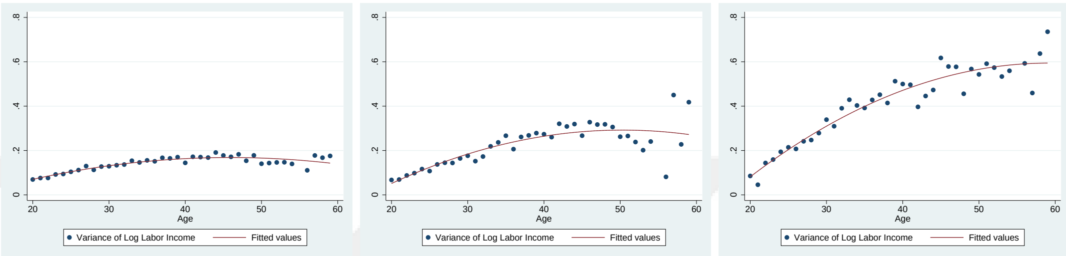


Figure 6. Labor income density based on sector

From the data, I know that the expected income in the private sector is higher than that in the public sector, but with higher risk and variance. Figure 7 shows that, only for high educated employees, there is a risk-return trade-off. With higher uncertainty, there exists a higher potential labor income in the private sector for university graduates. For low-qualified workers, there is no such trade-off; they are willing to find a job in the public sector because of the higher expected income and a similar level of volatility, but the number of available jobs in the public sector is very limited for low-educated individuals.



(a) Primary school (b) High school (c) University

Figure 7. Variance of log labor income in private sector

3.2.5 Gender

Figure 8 plots the labor income difference between male and female labor income. Both mean and median income is higher for male workers. For males, the labor income increases until age 40-44, after which point it remains remainly constant until retirement, whereas for females, the labor income increases up to age 30, and then the median income barely changes. For both genders, the labor income profile is quite flat after a certain age. I observe that the cross-sectional variance follows in an increasing fashion with age.

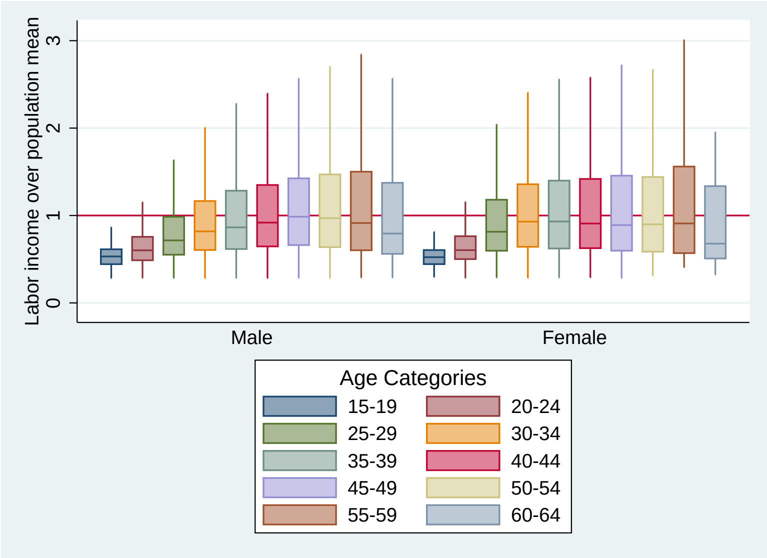
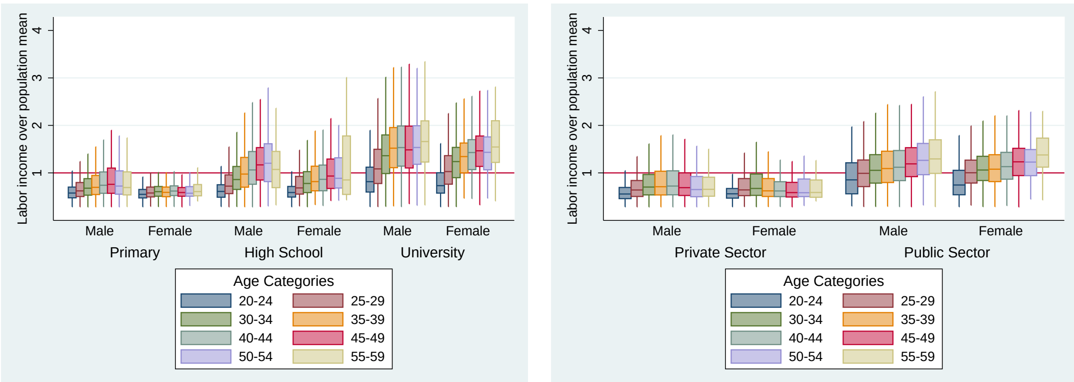


Figure 8. Labor income distribution based on gender

Figure 9 shows that increasing educational attainment increases the labor income for both genders, but in each education group, male labor income is higher than female labor income. Even in the public sector, the difference between genders is clearly visible, which provides evidence for the gender pay gap in Turkey.



(a) Gender-education clusters (b) Gender-sector clusters

Figure 9. Labor income distribution based on gender, education and sector

Wages for females who have primary or lower education are extremely low because women with low socioeconomic status tend to contribute to the household income by entering the low-qualified workforce as caretakers, cleaners or factory laborers. These women are usually employed in the informal sector without any social security. The shorter working hours for women in the private sector contributes to this difference as well. That is why for less educated groups the finding is not unexpected.

Only the female sample is considered in Figure 10 to show the differences between female clusters. There exists more visible risk-return trade-off for university graduates among females. Almost all who have primary or lower education earn less than the female population mean due to a high rate of informality in Turkey, especially for low paying jobs. The labor incomes in the private sector for those who have a high school or primary education do not change over the life cycle. In the public sector, labor income increases monotonically, as in the full sample, but the mean and median income are significantly lower for the female population in the public sector.

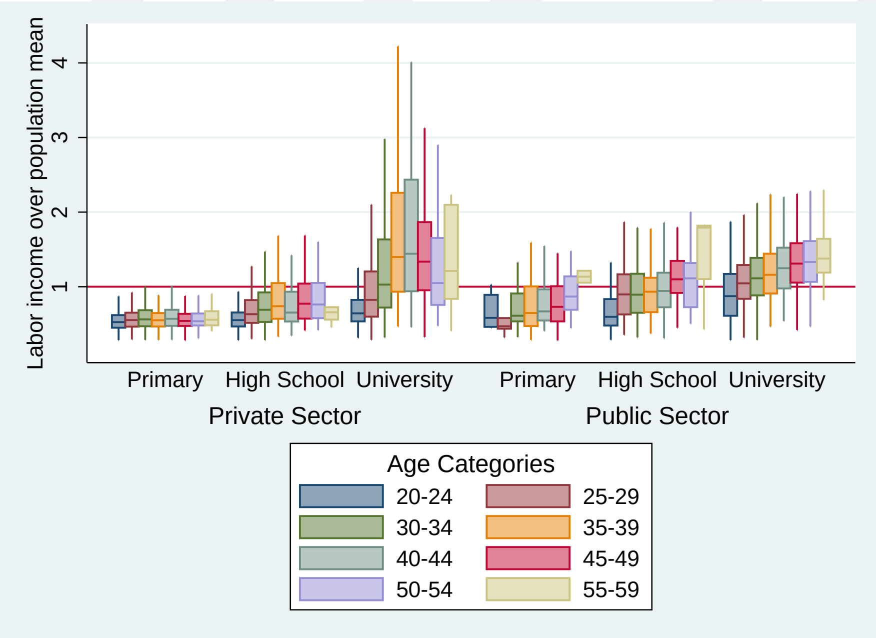


Figure 10. Labor income distribution based on education-sector clusters (Females only)

For the private sector, the pay gap might be explained by a vast range of skills suitable for specific work. Females with low skills and shorter working hours may dominate the private sector, resulting in a wage gap between genders. However, in the public sector, merit-based selection is the decisive mechanism, especially for educated employees. Both male and female university graduates with suitable skills are employed for similar positions, yet there is a visible gender pay gap.

CHAPTER 4

THE ESTIMATION METHOD

OLS is the main econometric analysis for this thesis. I use HBS data because it includes public-private sector employment as variable. However, as a robustness check, I also looked at Household Labour Force Survey and the results are highly consistent (see Appendix A). Additionally, the pseudo-panel analysis gives me another tool to check robustness. Since Turkish HBS data is composed of a series of independent cross-sections, I cannot observe the same individuals over years. Therefore, I am required to group individuals according to common characteristics (educational attainment, public-private sector employment, gender and year of birth) into cohorts. After that, I treat the averages within these cohorts as observations, which forms my pseudo-panel data.

The pseudo-panel method has many advantages for my purposes. In genuine panel data analysis, the main concern is the measurement error. The pseudo-panel approach reduces the measurement error bias due to the aggregation of individuals into cohorts. Yet, the bias and efficiency trade-off is significant here; increasing cohort size decreases measurement error and bias, but it decreases number of cohorts and decreases efficiency. That is why I define cohorts optimally, considering this trade-off.

The genuine panel data are subject to attrition and non-response bias, and that data spans short time periods such as 3 or 4 years for Turkish data. On the other hand, pseudo-panel data tends to suffer less from attrition and non-response bias, because each individual is observed only once. The data is often larger, both in terms of the number of individuals and in the time period it spans due to simply being repeated cross-sectional data (Verbeek, 2008). Pseudo-panel data may consist of systematic heteroscedasticity via aggregation. To prevent serious estimation errors, I weight each observation by a heteroscedasticity factor that is a function of cell size by following Gardes et al. (2005). Arguably, there are downsides of the pseudo-panel approach as well, such as loss of individual information due to aggregation, but for my purposes and data in hand, this is the best possible empirical approach, which is widely accepted in the literature.

Theoretically, the cohort size needs to go infinity to be able to treat pseudo-panel data as though they are genuine panels, so that conventional methods like fixed-effects estimator can be employed (Inoue, 2008). That is why cohort size should be sufficiently large. More than one hundred individuals in each cohort is suggested by Verbeek and Nijman (1992) to reduce the measurement error bias to a negligible degree. Since the measurement error becomes negligible only when cohort sizes are large (Moffitt, 1993) and HBS data is not large enough for Turkey, the minimum cohort size is set at 50, following Ziegelhofer's (2015) Monte Carlo Simulation outcomes. Ziegelhofer claims that the increasing bias resulting from decreasing the limit from 100 to 50 is not a significant amount for the estimation. At the same time, the number of total observations has to be large enough so that statistical efficiency can be obtained, which is 455 for my pseudo-panel data. That is to say, there is an obvious trade-off between cohort size and the number of cohorts (Verbeek, 2008). The larger the number of cohorts, the smaller is the cohort size, which leads to better estimation efficiency but higher measurement error. That is why I have applied some variations in cohort forming such as excluding both the public and the private sectors, but the results do not change much.

I create pseudo-panel data (a synthetic cohort panel) by grouping individuals in cohorts in line with criteria such as their birth year, educational attainment, gender, and public-private sector employment (Deaton, 1985). Birth year and gender are time-invariant, whereas education and sector can be time-varying for some observations. Since I am taking individual observations and grouping them together, I can safely take educational attainment and public-private sector employment as time-invariant variables as well.

For each cohort and each year, I calculate the mean of log income. My synthetic data includes 59 cohorts, 13 time periods and an average cohort size of 158. There are 455 observations, which is less than 59x13, because the pseudo-panel is not balanced owing to an insufficient number of observations for extreme groups in some years. If only one year of data exists for a cohort, I exclude this cohort because it lacks the panel property.

I restrict the sample to individuals aged between 20 and 60 to target the working population. As before, those who earn less than the minimum wage can be considered unemployed and are therefore dropped from the sample. I create groups by birth year with a 5-year span starting from 1950-1954 to 1985-1989, a total of 8 groups. I use a static linear model with cohort fixed-effects as follows:

$$\bar{y}_{ct} = \bar{x}_{ct}\beta + \bar{\theta}_c + \bar{\varepsilon}_{ct} \tag{1}$$

where c denotes the cohorts, $\bar{y}_{ct}$ are the cohort wage income average and $\bar{x}_{ct}$ are the cohort averages. Since each cohort consists of different members in each year, the cohort effect is time varying as $\bar{\theta}_{ct}$. According to Verbeek and Nijman (1992) with a sufficiently large cohort size the time varying $\bar{\theta}_{ct}$ can be treated as constant over time, which is $\bar{\theta}_c$ in regression. The reason is that clustering similar individuals into cohorts tends to homogenize individual effects among individuals grouped in the same cohort, so that average individual effect that is simply cohort effect is approximately time-invariant (Ziegelhofer, 2015). Thus, it is possible to use conventional estimation tools such as fixed-effects estimator.

CHAPTER 5

RESULTS

The hump-shaped profile over age is obvious, with a peak at age 40-44, which is not clear in the descriptive analysis part due to not controlling for years, as shown in Table 1. As expected, increasing years of education leads to higher wages for workers. Consistent with my risk-return trade-off analysis, the public sector pays more on average. A gender pay gap exists with high statistical significance.

Table 1. OLS for Labor Income

	(1) ln(Labor Income)	(2) ln(Labor Income)
Age		
25 to 29	0.114***	0.108***
	(0.006)	(0.006)
30 to 34	0.199***	0.193***
	(0.006)	(0.006)
35 to 39	0.239***	0.230***
	(0.006)	(0.006)
40 to 44	0.242***	0.228***
	(0.007)	(0.007)
45 to 49	0.232***	0.216***
	(0.008)	(0.008)
50 to 54	0.195***	0.174***
	(0.010)	(0.009)
55 to 59	0.171***	0.156***
	(0.014)	(0.014)
Years of Education		
6-8	0.089***	0.092***
	(0.005)	(0.006)
9-12	0.221***	0.213***
	(0.004)	(0.005)
13-14	0.356***	0.339***
	(0.007)	(0.012)
15-16	0.549***	0.756***
	(0.007)	(0.012)
17+	0.936***	1.200***
	(0.021)	(0.048)
Sector(Public=1)	0.108***	0.228***
	(0.005)	(0.009)
Education-Sector Interaction		
6-8 × Public Sector		-0.071***
		(0.013)
9-12 × Public Sector		-0.057***
		(0.010)
13-14 × Public Sector		-0.070***
		(0.016)
15-16 × Public Sector		-0.406***
		(0.015)
17+ × Public Sector		-0.470***
		(0.052)
Gender(Female=1)	-0.139***	-0.135***
	(0.004)	(0.004)
Union(Member=1)	-0.167***	-0.163***
	(0.005)	(0.005)
Area(Urban=1)	0.091***	0.095***
	(0.004)	(0.004)
Tenure	0.011***	0.011***
	(0.000)	(0.000)
Year Dummies	Yes	Yes
N	53878	53878

Note: Numbers in parentheses are standard errors. * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. Age 20-24 is the basis.

Dividing the full sample into sub-samples gives more interesting results. In Table 2, I can see that all education groups follow a hump-shaped labor income profile over the life cycle but with different peak ages. The peak is at age 40-44 and 35-39 for primary and high school graduates, respectively. However, for university graduates the age effect is nearly the same after age 35, regardless of gender. For male university graduates, the public sector pays less, with high statistical significance, but the significance disappears for females. Jobs in urban areas also pay more for males, but interestingly, the statistical significance vanishes for females. This might be due to the high portion of low-qualified workers in the female sample. More surprisingly, being a union member negatively affects the labor income for primary school graduates. Changing the sample from above minimum wage earners to all positive wage earners does not change the result. In addition, the effect of union membership is negligible for university graduates.

Table 2. OLS for Labor Income Based on Education and Gender

	Male			Female		
	Primary	High School	University	Primary	High School	University
Age						
25 to 29	0.081***	0.145***	0.189***	0.022	0.166***	0.214***
	(0.009)	(0.011)	(0.042)	(0.017)	(0.016)	(0.029)
30 to 34	0.133***	0.248***	0.419***	0.031	0.174***	0.346***
	(0.009)	(0.011)	(0.042)	(0.018)	(0.018)	(0.032)
35 to 39	0.148***	0.297***	0.529***	-0.006	0.197***	0.419***
	(0.009)	(0.013)	(0.043)	(0.016)	(0.022)	(0.036)
40 to 44	0.157***	0.283***	0.519***	0.014	0.156***	0.448***
	(0.009)	(0.014)	(0.046)	(0.017)	(0.025)	(0.045)
45 to 49	0.136***	0.265***	0.523***	-0.038*	0.213***	0.484***
	(0.010)	(0.016)	(0.049)	(0.018)	(0.034)	(0.052)
50 to 54	0.100***	0.217***	0.492***	-0.039	0.163***	0.414***
	(0.012)	(0.020)	(0.052)	(0.028)	(0.043)	(0.069)
55 to 59	0.066***	0.211***	0.536***	-0.051	0.028	0.451***
	(0.017)	(0.034)	(0.062)	(0.046)	(0.108)	(0.111)
Sector(Public=1)	0.191***	0.142***	-0.146***	0.149***	0.179***	-0.049*
	(0.008)	(0.009)	(0.018)	(0.028)	(0.017)	(0.023)
Union(Member=1)	-0.326***	-0.144***	0.040***	-0.237***	-0.130***	-0.002
	(0.010)	(0.008)	(0.012)	(0.037)	(0.016)	(0.015)
Area(Urban=1)	0.113***	0.087***	0.066***	0.027	0.056**	0.039
	(0.006)	(0.009)	(0.019)	(0.017)	(0.018)	(0.027)
Tenure	0.009***	0.016***	0.005***	0.013***	0.015***	0.005*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	23545	15138	5745	2521	3946	2983

Note: Numbers in parentheses are standard errors. * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. Age 20-24 is the basis.

In Table 3, I can see the effect of public-private sector employment more clearly. University graduates in the private sector earn more than those in the public sector until age 50. This reflects the risk-return trade-off in Turkey. The expected income is higher in the private sector, but the volatility is higher as well in the private sector for both university and high school graduates, as shown in the descriptive analysis part. The hump-shaped labor income profile over age is obvious for university graduates in the private sector, with the peak at age 35-39, whereas an increasing profile exists for those in the public sector. Importantly, the increasing profile exists only for university graduates, not for primary or high school graduates. For them, the profile is quite flat over age.

Table 3. OLS for Labor Income Based on Education and Sector

	Private Sector			Public Sector		
	Primary	High School	University	Primary	High School	University
Age						
25 to 29	0.068***	0.121***	0.178***	0.028	0.145***	0.172***
	(0.008)	(0.009)	(0.037)	(0.069)	(0.028)	(0.028)
30 to 34	0.118***	0.209***	0.435***	0.128	0.155***	0.288***
	(0.008)	(0.011)	(0.041)	(0.066)	(0.027)	(0.028)
35 to 39	0.132***	0.279***	0.638***	0.138*	0.162***	0.358***
	(0.008)	(0.015)	(0.046)	(0.065)	(0.028)	(0.030)
40 to 44	0.139***	0.293***	0.580***	0.140*	0.142***	0.398***
	(0.009)	(0.018)	(0.057)	(0.065)	(0.029)	(0.032)
45 to 49	0.098***	0.272***	0.590***	0.136*	0.156***	0.439***
	(0.010)	(0.022)	(0.067)	(0.066)	(0.031)	(0.036)
50 to 54	0.058***	0.192***	0.348***	0.117	0.134***	0.475***
	(0.012)	(0.029)	(0.067)	(0.067)	(0.034)	(0.039)
55 to 59	0.051**	0.209***	0.455***	0.022	0.086*	0.525***
	(0.017)	(0.054)	(0.101)	(0.072)	(0.043)	(0.047)
Gender(Female=1)	-0.154***	-0.068***	-0.153***	-0.176***	-0.120***	-0.128***
	(0.006)	(0.009)	(0.024)	(0.025)	(0.010)	(0.009)
Union(Member=1)	-0.305***	-0.242***	-0.152**	-0.303***	-0.091***	0.041***
	(0.015)	(0.014)	(0.055)	(0.012)	(0.008)	(0.009)
Area(Urban=1)	0.082***	0.087***	0.177**	0.173***	0.081***	0.050***
	(0.006)	(0.012)	(0.064)	(0.013)	(0.010)	(0.012)
Tenure	0.006***	0.023***	0.026***	0.018***	0.013***	-0.000
	(0.000)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	21791	11320	2846	4275	7764	5882

Note: Numbers in parentheses are standard errors. * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. Age 20-24 is the basis.

The pseudo-panel analysis also provides results that are consistent with OLS and the descriptive analysis. I conduct a fixed-effects regression without any sector specification at the cohort level. That is why it is impossible to estimate the effect of public-private sector on labor income under this specification. Since the explanatory variables should be time-varying in fixed-effects estimator, I interact the age variable with time-invariant characteristics in the regressions. I take the log of labor income for regressions.[9]

[9] The base levels of factor variables are dropped from the regression table.

Table 4 demonstrates that the general labor income profile tends to be hump-shaped across age groups because coefficients of age and age-squared are positive and negative respectively. The coefficient of age varies slightly with the addition of new variables. Moreover, the presence of the education premium is statistically verified both for high school and university graduates. The impact of university education is nearly three times as high as the impact of high school education.[10] However, getting a high school education is significant at the 5% level when I include gender as an explanatory variable. In addition, the gender pay gap is significant at the 1% level, and the magnitude is relatively high, which reflects the economic significance.

Table 4. Pseudo-Panel Estimation

	Labor Income			
	(1)	(2)	(3)	(4)
Age	0.1717***	0.1912***	0.1595***	0.1807***
	(25.61)	(26.57)	(25.29)	(26.69)
Age^2	-0.0017***	-0.0018***	-0.0017***	-0.0019***
	(-18.63)	(-20.34)	(-21.26)	(-23.36)
Female × Age		-0.0205***		-0.0202***
		(-6.02)		(-6.70)
High School × Age			0.0141***	0.0107**
			(3.98)	(3.13)
University × Age			0.0386***	0.0380***
			(10.90)	(11.30)
Fixed effects	yes	yes	yes	yes
N	455	455	455	455
R-Squared	0.76	0.78	0.82	0.85

Note: Numbers in parentheses are standard errors. * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. Age 20-24 is the basis.

Finally, I look at permanent and transitory annual earnings of the synthetic cohorts by following the analysis of Moffitt (1993). Table 5 demonstrates that the variance of permanent labor income increased after the 2008 financial crisis for university graduates whereas for primary and high school graduates, it declined. The variance increased for every age group. The ones with lower real income experienced a lower volatility after the crisis, but for high earners, the volatility of income increased. On

[10] $e^x = 1 + x$ for small values of x. Since I consider the log of labor income, to measure the impact of a one-unit increase in an independent variable the approximation can be safely used, due to the small values of the coefficients.

the other hand, the variance of transitory earnings has declined for all groups, and this decline is more severe for the lower educated ones and lower earners. In general, I can see that, after the crisis, the volatility of labor income declined for most of the sample.

Table 5. Variances of Permanent and Transitory Real Labor Income, 2002-2014

	Permanent Variance			Transitory Variance		
Sample Definition	2002-08	2009-2014	Change	2002-08	2009-2014	Change
All	0.311	0.333	7%	0.160	0.094	-41%
Education						
Primary School	0.179	0.134	-25%	0.148	0.067	-54%
High School	0.248	0.227	-8%	0.162	0.098	-39%
University	0.223	0.251	12%	0.172	0.118	-31%
Age						
25-34	0.242	0.256	5%	0.153	0.092	-39%
35-44	0.290	0.340	17%	0.143	0.075	-47%
45-54	0.289	0.358	23%	0.109	0.081	-25%
Earnings %						
Lowest 33 percent	0.086	0.079	-8%	0.127	0.061	-51%
33-66 percent	0.068	0.085	25%	0.072	0.058	-19%
Top 66 percent	0.153	0.175	14%	0.109	0.096	-12%

Variances are for log annual earnings adjusted to 2014 liras

CHAPTER 6

CONCLUSION

The labor income profiles in Turkey follow very different paths, depending on the characteristics of individuals. Except for the university graduates who are employed in the private sector, all other groups experience a hump-shaped labor income profile over their life cycles, consistent with profiles in the developed countries. As expected, there is a very significant education premium, along with a risk-return trade-off between sectors and a gender pay gap, which are shown both descriptively and empirically. Most importantly, the risk-return trade-off is visible among university graduates; those who are in the private sector earn more on average, but the volatility is very high over the life cycle. Both datasets provide highly consistent outcomes and verify the existence of these phenomena. Pseudo-panel estimation gives results that are similar to those of OLS, but the pseudo-panel approach does not perform well under further specifications due to the low number of observations that result from clustering. However, this approach is useful for an age-period-cohort analysis; I observe that the period (year) effect is following an increasing trend over year, but the age effect is quite flat after age 40. The cohort effect is very volatile over years, but on average the effect increases, which means that, on average, under same conditions younger cohorts earn more.

APPENDIX A

OLS ANALYSIS USING TURKISH HOUSEHOLD LABOUR FORCE SURVEY

Table A1. OLS for Wage

	(1) Wage	(2) Wage
Age		
25 to 29	0.096***	0.094***
	(0.002)	(0.002)
30 to 34	0.169***	0.168***
	(0.002)	(0.002)
35 to 39	0.210***	0.209***
	(0.002)	(0.002)
40 to 44	0.223***	0.221***
	(0.003)	(0.003)
45 to 49	0.219***	0.214***
	(0.003)	(0.003)
50 to 54	0.219***	0.213***
	(0.003)	(0.003)
55 to 59	0.199***	0.195***
	(0.005)	(0.005)
Years of Education		
6-8	0.071***	0.070***
	(0.002)	(0.002)
9-12	0.175***	0.155***
	(0.002)	(0.002)
13+	0.534***	0.564***
	(0.002)	(0.003)
Sector(Public=1)	0.283***	0.280***
	(0.002)	(0.004)
Education-Sector Interaction		
6-8 × Public Sector		0.005
		(0.005)
9-12 × Public Sector		0.082***
		(0.004)
13+ × Public Sector		-0.048***
		(0.005)
Gender(Female=1)	-0.134***	-0.134***
	(0.001)	(0.001)
Tenure	0.009***	0.009***
	(0.000)	(0.000)
Year Dummies	Yes	Yes
District Dummies	Yes	Yes
N	336484	336484

Note: Numbers in parentheses are standard errors. * for $p < .05$, ** for $p < .01$, and *** for $p < .001$.

Table A2. OLS for Wage Based on Education and Gender

	Male			Female		
	Primary	High School	University	Primary	High School	University
Age						
25 to 29	0.037***	0.064***	0.219***	0.020***	0.052***	0.238***
	(0.003)	(0.004)	(0.007)	(0.005)	(0.006)	(0.007)
30 to 34	0.056***	0.123***	0.376***	0.026***	0.110***	0.358***
	(0.003)	(0.004)	(0.007)	(0.005)	(0.006)	(0.007)
35 to 39	0.065***	0.176***	0.493***	0.015**	0.123***	0.425***
	(0.003)	(0.004)	(0.008)	(0.005)	(0.008)	(0.009)
40 to 44	0.073***	0.198***	0.536***	0.010*	0.089***	0.469***
	(0.003)	(0.005)	(0.009)	(0.005)	(0.009)	(0.011)
45 to 49	0.084***	0.160***	0.531***	0.002	0.049***	0.475***
	(0.003)	(0.006)	(0.010)	(0.006)	(0.012)	(0.014)
50 to 54	0.085***	0.152***	0.526***	0.008	0.069***	0.452***
	(0.004)	(0.007)	(0.012)	(0.008)	(0.021)	(0.016)
55 to 59	0.084***	0.109***	0.496***	0.030*	0.134**	0.400***
	(0.006)	(0.011)	(0.014)	(0.013)	(0.045)	(0.024)
Sector(Public=1)	0.320***	0.342***	0.250***	0.235***	0.301***	0.226***
	(0.003)	(0.004)	(0.005)	(0.012)	(0.007)	(0.005)
Area(Urban=1)	0.017***	0.038***	0.064***	0.007	0.031***	0.031***
	(0.002)	(0.003)	(0.005)	(0.004)	(0.007)	(0.007)
Tenure	0.007***	0.014***	0.002***	0.009***	0.016***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
District Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	1.2e+05	7.3e+04	6.6e+04	1.6e+04	1.8e+04	3.8e+04

Note: Numbers in parentheses are standard errors. * for $p < .05$, ** for $p < .01$, and *** for $p < .001$.

APPENDIX B

AGE-PERIOD-COHORT (APC) ANALYSIS

To understand the time-varying components in the life cycle income analysis, I need to look at age, period and cohort effects. Age effects are variations linked to the social processes of aging specific to individuals, but unrelated to the time period and birth cohort. Period effects are the sum of all external factors that equally influence all age groups at a certain year.[11] Finally, cohort effects result from the unique experience of each cohort as time goes by. Age-Period-Cohort (APC) analysis allows me to disentangle the independent effect of these factors and to estimate the effects of age, period and cohort effects separately.

Figures B1 and Figure B2 are useful for qualitative impressions about temporal patterns. Since the shape of the birth cohort curve is affected by both varying age effects and period effects, they do not provide an accurate quantitative evaluation of the sources of change. Each graph describes only the variation in the labor income that is attributed to factors associated with either age or year. From Figure B1, I expect to see a positive cohort effect for the younger generations because, in a particular age group, younger cohorts earn more. However, the year effect might be also responsible for this difference. Thus, there is a need for statistical regression modelling to capture how these three effects work simultaneously.

[11] Social, economic and environmental factors such as wars, natural disasters, and crises.

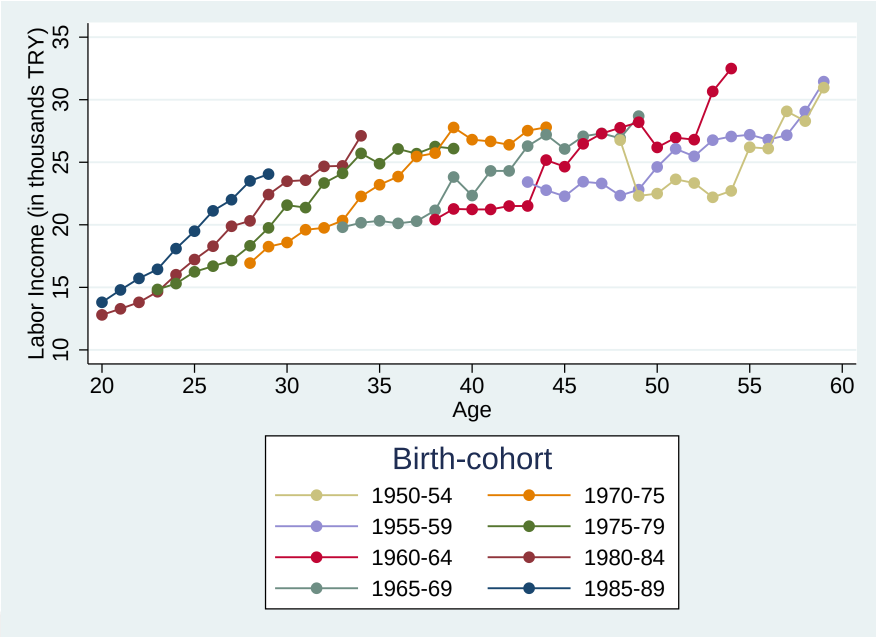


Figure B1. Labor income over life cycle by birth-cohort

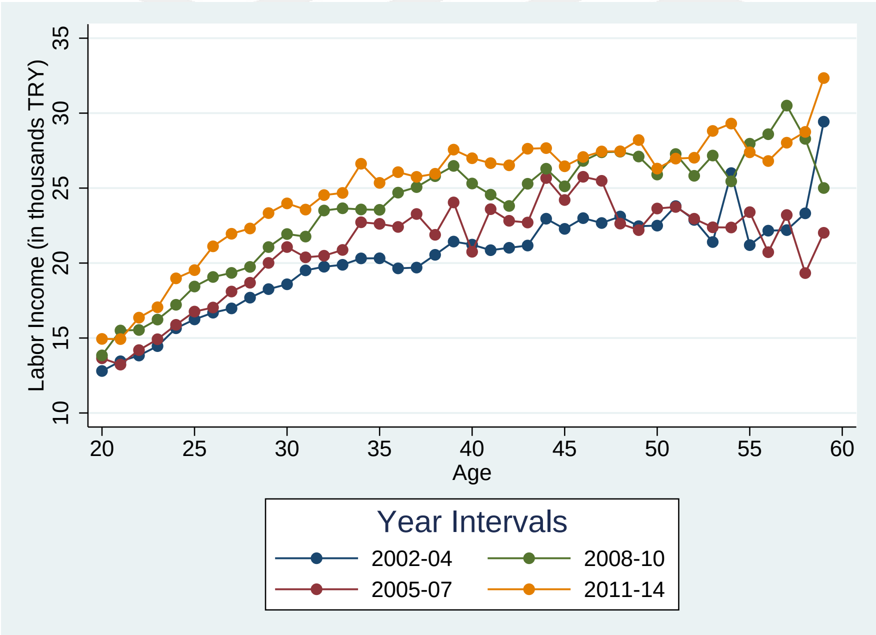


Figure B2. Labor income over life cycle by time periods

The main impediment to estimate the independent effect of age, period and cohort is the identification problem resulting from these three effects being perfectly collinear (cohort=year-age), i.e. given any two of them, one can determine the third one.

$$W_{ij} = \mu + \alpha_i + \beta_j + \gamma_k + \varepsilon_{ij} \tag{2}$$

where W_{ij} denotes the observed mean labor income values for the ith age group for i=20,...,60 at the jth year for j=2002,...,2014. μ stands for the intercept or adjusted mean labor income, α_i is the coefficient for the ith age group, β_j is the coefficient for the jth year, γ_k is the coefficient for the kth cohort for k=1942,...,1995 and ε_{ij} is set as white noise.

After reparametrization as follows,

$$\sum_i \alpha_i = \sum_j \beta_j = \sum_k \gamma_k = 0 \tag{3}$$

the model (2) can be written in the following matrix form:

$$Y = Xb + \varepsilon \tag{4}$$

where Y is a vector of mean labor income values, X is the design matrix consisting of dummy variable column vectors (Yang, 2013) and ε is a vector of random errors with mean 0. Parameter b is defined as follows:

$$b = (\mu, \alpha_{20}, ..., \alpha_{59}, \beta_{2002}, ..., \beta_{2013}, \gamma_{1942}, ..., \gamma_{1992})^T \tag{5}$$

It is important to note that $\alpha_{60}, \beta_{2014}$ and γ_{1993} are excluded from (5) so that constraint (3) can be satisfied. The identification problem is clear when I reformulate (4):

$$\hat{b} = (X^T X)^{-1} X^T Y \tag{6}$$

Due to age, period and cohort all being collinear, the design matrix X is one less than full-column rank. Since the inverse of this singular matrix does not exist, it is not possible to estimate age, period or cohort effects without any further restrictions or constraints. That is why the main purpose is to break the linear dependency between these three effects. There are many solutions[12] to the identification problem, but in this paper, I will consider the most recent technique, the intrinsic estimator (Yang, 2013).

The parameter space of the unconstrained model (4) can be decomposed into two orthogonal linear subspaces and formalized as follows:

$$b = b_0 + sB_0 \tag{7}$$

where $b_0 = P_{proj}b$ is the projection of the b to nonnull space of X. B_0 is a unique eigenvector and depends only on matrix X, which is determined by number of age groups and periods. The intrinsic estimator imposes a constraint on the geometric orientation of the parameter b: the eigenvector B_0 in the null space of X has no influence on the parameter b_0. Since B_0 does not depend on observed values, it is a sensible constraint.

$$B = (I - B_0 B_0^T)\hat{b} \tag{8}$$

I first estimate $\hat{b}$ of model (4) and project $\hat{b}$ on the intrinsic estimator B by removing the component in the B_0 direction (Yang, 2013).

$$X\hat{b} = X(B + tB_0) = XB + 0 = XB \tag{9}$$

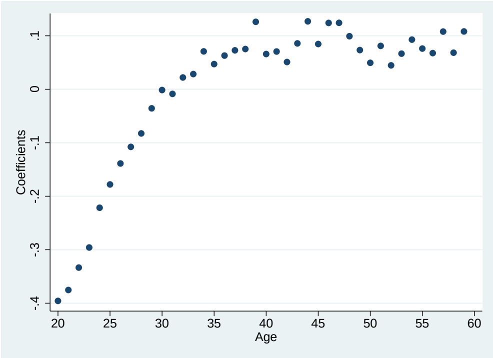
[12]Reduced two-factor models, constraint generalized linear models, non-linear transformation, and proxy variables are some of the solutions.

In short, intrinsic estimator allows me to estimate the projection of the unconstrained vector on the nonnull space of the matrix X by removing the influence of null space.[13]

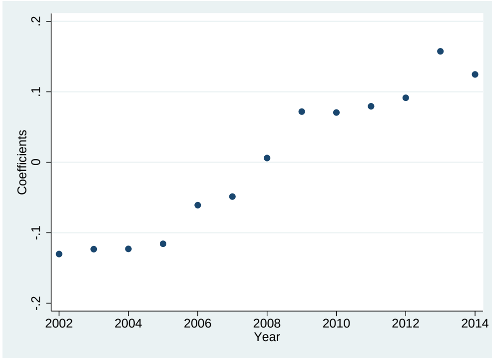
For robustness, I use the conventional approach to APC models, that is, the coefficient constraints approach. As the identifying constraint on the parameter vector *b* in equation (5), the equality of the effect coefficients of the first two periods is imposed as the only constraint that makes the matrix $(X^T X)$ in equation (6) non-singular and allows the estimation of the effects separately. The results are consistent with the outcomes of the intrinsic estimator approach.[14]

The age effects are consistent with my findings: the labor income is increasing rapidly until age 35 and stays nearly the same, with small oscillations until age 60 for the working population. At the same time, I see a monotonic increase for the period effects in Figure B3. Since the Turkish economy is constantly growing (with the exception of the year 2009), the year effect on labor income increases over time. Finally, as shown in Figure B4, the cohort effect shows an increasing trend, where some cycles are without any particular path. Since the share of university and high school graduates in the population increases with younger cohorts, I expect to see a higher cohort effect for younger cohorts. That is consistent with the data shown Figure B1 because, at a particular age, younger cohorts earn more than the previous cohort. The decrease at the end of the graph is due to the cohorts that are still in the education process. Similarly, the increasing period effect is consistent with the data in Figure B2 because the real labor income increases over the years due to positive GDP growth.

[13]I use the *apc_ie* command in Stata to estimate age, period and cohort effects.
[14]However, changing the constraint can produce widely different estimates for the effects.



(a) Age effects



(b) Period effects

Figure B3. Effect coefficients

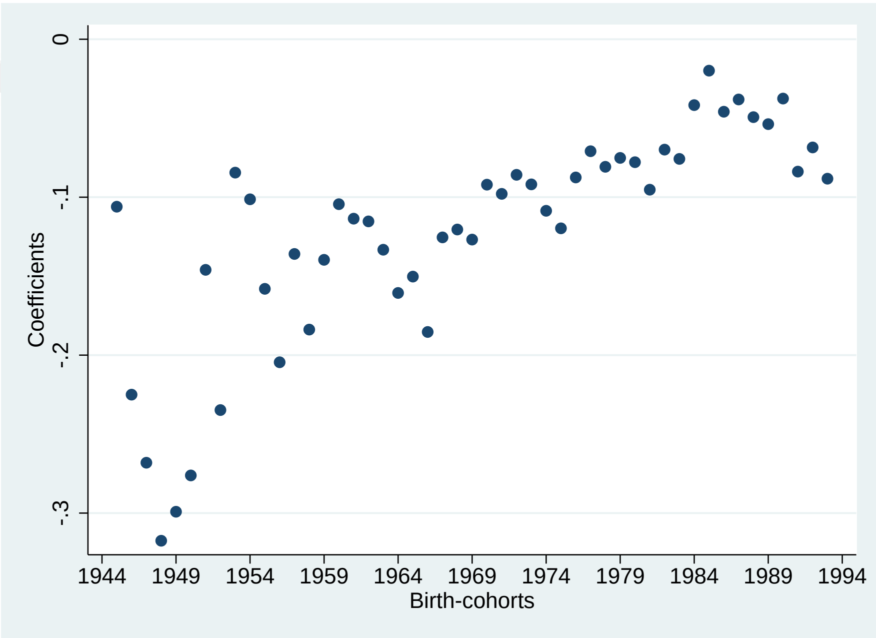


Figure B4. Cohort effects

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