ERF 2020

26TH Annual Conference

The Impact of Age-specific Minimum Wages on Youth Employment and Education: A Regression Discontinuity Analysis

Meltem Dayioglu Tayfur,
Müserref Küçükbayrak and Semih Tumen

ECONOMIC RESEARCH FORUM

The impact of age-specific minimum wages on youth employment and education: A regression discontinuity analysis *

Meltem Dayioglu Tayfur †
Middle East Technical University
dmeltem@metu.edu.tr

Muserref Kucukbayrak ‡
Central Bank of the Republic of Turkey
muserref.kucukbayrak@tcmb.gov.tr

Semih Tumen §
TED University, IZA, and ERF
semih.tumen@tedu.edu.tr

February 24, 2020

Abstract

We exploit the age-specific minimum wage rule—which sets a lower minimum wage for workers of age 15 than that for workers of age 16 and above—to estimate its effects on youth employment and education in Turkey. Using a regression discontinuity approach, we find that youth minimum wage policy substantially reduced employment probabilities of young males. In terms of magnitudes, the employment probability declined by 2-4 percentage points for salaried workers and 3-5 percentage points for all at 16-year-old age cut-off. Due to the policy, probability of unemployment increased around 2 percentage points. Our findings also suggest that the policy change increased high school enrollment among young males. We conjecture that the effects of the policy have mostly been driven by the demand-side forces rather than the supply side.

JEL codes: J21; J24; J31; J38.
Keywords: Age-specific minimum wages; youth employment; education; regression discontinuity design.

*We thank Hakan Ercan, Julide Yildirim Ocal, Nur Asena Caner, Erol Taymaz and the seminar participants at the Middle East Technical University and TED University Trade Research Center 2019 Conference for useful comments and suggestions. The views expressed here are of our own and do not necessarily reflect those of the Central Bank of the Republic of Turkey. All errors are ours.

†Middle East Technical University, Department of Economics. Universiteler Mah., Dumlupınar Bul., No.1, 06800 Cankaya, Ankara.

‡Central Bank of the Republic of Turkey, Structural Economic Research Department. Istiklal Caddesi No.10, 06050 Ulus, Ankara, Turkey.

§TED University, Department of Economics. Ziya Gokalp Cad., No.48, 06420 Kolej, Ankara, Turkey.

1 Introduction

Extensive literature on minimum wage is broadly concentrated on developed economies, drawing less attention to developing ones. Yet, economics of minimum wage in developing countries might be different (Lemos, 2009). Since relatively more workers are earning at or around the minimum wage level, it affects a larger domain in developing economies. In the meanwhile, high degrees of informality and non-compliance to minimum wage rule prevail. Therefore, the impact of minimum wage on labor market become controversial. As implied by two-sector model, minimum wage might depress average wages in informal part of the labor market in developing countries (Mincer, 1976). However, empirical evidence suggests that minimum wage policy can create spillover effects so that it increases wage rates even in the parts in which minimum wage does not apply (Del Carpio and Pabon, 2017). Acting as a reference price for wage setting processes in all parts of the labor market[1], minimum wage can influence labor markets in different ways in developing economies.

Presence of potential spillover effects necessitates a careful analysis of minimum wage effects in developing economies like Turkey. Despite the economy wide mandated coverage of the minimum wage policy, its applicability remains limited in the country because of the extensive informality in labor market. In Turkey, 17.6% of male wage earners were working without social security in 2017. Furthermore, the incidence of informality is much higher among youth. In the same year, rate of informality was 59.5% for 15-19-year-old males and was 86.3% for 15-16-year-old males. On the other hand, a significant share of workers in the country work at or around the minimum wage. Based on the official records of Social Security Institution, 34.7% of male wage earners were paid at the minimum level. Moreover, according to Household Labor Force Survey (HLFS), while 11.8% of 15-16-year-old male wage earners received minimum wage in 2017, 22.3% of 15-19-year-old corresponding males earned at the minimum wage level. Hence, whether minimum pay policies significantly affect the Turkish labor market, especially the youth, is a credible inquiry.

In this paper, we study the impact of age-specific structure of minimum wage on youth

[1] There are other explanations for how minimum wage increases average wages in the informal labor markets available in literature [see for example Boeri et al. (2011) and Fiszbein (1992)].

employment and education in Turkey. Prior to 1 January 2014, minimum wage in the country was determined based on the age of workers. There was a single age cut-off. Particularly, workers under 16 were entitled to receive the youth rate, whereas the adult rate paid to older workers. The differential between amounts received by each group was almost stable around 15% of the adult rate since 1994. The official authority decided to abolish this rule at the end of 2013. This policy was purely exogenous because no media discussion or policy debate had been made before. The age-based rule is key to the Regression Discontinuity (RD) design we use in this paper. We analyze the impact of minimum wage among 15-16-year-old males based on this rule before January 2014, which provides a quasi-experiment applicable to conventional sharp RD design.

We use 2014-2015 waves of Turkish Survey of Income and Living Conditions (SILC). This micro-level longitudinal data set enables us to follow main activity of individuals in each month of 2013-2014. Besides, we compute "age in months", which is a key object in our empirical design, by using month and year of birth information available in the data. We restrict our sample to 15-16-year-old males. Firstly, individuals under 15 are not legally allowed to work in Turkey. Secondly, we do not include males above 17 to avoid differential treatment of individuals on both sides of 16-year-old age cutoff. Finally, social, cultural or religious factors might be more influential than the economic factors on the behavior of young females.

We find that youth minimum wage policy in Turkey reduces employment probabilities of young males. In terms of magnitudes, the probability of being a salaried worker declines by 2-4 percentage point (pp) as young males pass 16-year-old age cut-off. The corresponding decline is 3-5 pp for employment probability in any type. We interpret the reduction of youth employment based on a demand side story. Before 2014, males under 16 years old were 15% cheaper on average compared to their older counterparts. This provided them an advantage while competing with older males for the same type of jobs. Our findings also suggest that a higher minimum wage increases unemployment and school participation of the young males. These results suggest that after losing their jobs, some of the males either become unemployed and queue for higher paying jobs, or enroll school. The magnitude of the policy impact is around 2 pp for unemployment and 1-2 pp for education. Moreover, minimum wage increases the probability of young males being neither in employment nor in education.

The plan of the paper is as follows. Section 2 briefly summarizes the relevant empirical literature. Section 3 presents the background on the youth minimum wage policy in Turkey. Section 4 describes data and identification strategy. Section 5 discusses empirical findings. Section 6 concludes.

2 Related literature

How minimum wage policies affect labor markets is extensively scrutinized by the empirical world. Although there are plenty of studies analyzing the effects of minimum wage on young labor, very few are addressing the impact of age-specific policies. Indeed, the empirical literature mostly focus on the impact of general minimum wage policies, adopting uniform rates for all ages, on young individuals.[2] Uniform minimum wage rates might discourage firms from employing younger individuals who are less skilled and less experienced. On the other hand, creating price differentials among labor of different age groups, age-specific policies might change composition of workers hired in favor of younger labor. This is why we presume that minimum wage policies with age-specific structure might affect young labor in different ways and we intend to analyze such policies in this study.

Studies on minimum wage effects under age-specific policies usually use difference-in-differences (DID) design to analyze them. Using the abolition of youth minimum wage rate applied to 18-19-year-old workers in 1987 Pereira (2003) finds adverse employment effects for this age group in Portugal. Portugal and Cardoso (2006) exploit the same experiment, but they analyze the minimum wage effects on 17-19-year-old workers, which is possible because youth rate also increased for 17-year-old workers in the same year. Yannelis (2014) shows that the introduction of age-specific minimum wage scheme offering lower rate for workers under 25 years old, increases the rate of new hires among young workers exposed to lower minimum wage rate in Greece. Hyslop and Stillman (2007) utilize the reform altering the age structure of youth minimum wage and its rate in New Zealand. Specifically, the age group exposed to youth rate was narrowed from 18-19-year-

[2] see, e.g., Allegretto et al. (2011), Sen and Waal (2011), Gorry (2013), Neumark and Wascher (2014), Liu and Regmi (2016).

old workers to 16-17-year-old workers. They find adverse effects on youth employment two years after the reform, despite zero effect in the shorter run. Based on the abolition of youth minimum wage rates in six provinces of Canada, Shannon (2011) examines the impact of minimum wage on employment and hours of worked of 15-16-year-old workers.

Another methodology used by researchers is to follow an RD design in analyzing the impact of age-specific minimum wages on youth. Exploiting the discontinuities of a stepwise minimum wage structure in Netherlands Kabatek (2015) analyzes the impact of this policy on 15-23-year-old workers. His results indicate a significant increase in the job separation rates around the discontinuity points. Similarly, Olssen (2011) questions how a 10% increase in minimum wage for each year until age 21 affects employment of 15-21-year-old workers in Australia. Kreiner et al. (2017) analyze the impact of age-specific minimum wages in Denmark offering a youth rate for the workers under 18. They find that as workers turn 18, 40% increase in the amount of minimum pay reduces employment rate by 15 pp. Using the existence of the youth rate for workers under 22 in UK, Fidrmuc and Tena (2018) provide a support to adverse employment effects on young males. Dickens et al. (2014) also follow a similar methodology based on the UK experiment. Yet, they end up with different findings. Dickens et al. (2014) show that youth minimum pay policy increases employment and activity rates of low-skilled youth.

Youth minimum wage literature differs from the literature focusing on the effect of minimum wage on adults. It is because schooling can be an option for young labor so that their decision on labor market participation are determined together with education opportunities. As such, debates on the impact of minimum wage policy flared because human capital theory does not unambiguously predict its effects on the schooling outcomes. The idea is as follows. Statutory minimum wages might compress wage distribution so that it can increase the wages rates of young workers on the lower end of wage distribution (Acemoglu, 2001). On the one hand, higher wages available to young labor increase the opportunity cost of schooling thereby preventing some of them from participating to school (Belman and Wolfson, 2014). Besides, better labor market opportunities might create an incentive for them to participate in labor markets. On the other hand, if minimum wage reduces chances of job finding for youth, then the cost of foregone work will decline instead, thereby increasing school participation due to the increase in expected return to schooling (Pacheco and Cruickshank, 2007). Empirical evidence reports mixed results concordantly. Neumark and Wascher (1995a,b,c, 2003), studying the relation between minimum wage, employment and school enrollment based on the US experience, find that minimum pay policies lead students to leave school to queue for minimum wage jobs. Similarly, Pacheco and Cruickshank (2007) find that increases in minimum amount of pay reduces the enrollment levels of 16-19-year-olds in New Zealand. On the other hand, employing Canadian data over 1993-1999, Campolieti et al. (2005) show that minimum wage do not significantly affect school enrollment of young people. Crofton et al. (2009) find that minimum wage is not significantly related with the dropout rates, except Hispanic students.

Many studies analyze whether minimum pay policies significantly affect young labor, but its impact is less well studied in developing economies. However, it might affect labor markets in these countries differently. Developing countries mostly have different economic environments compared to more advanced economies (Lemos, 2009). In particular, minimum wages are often set high and, a great amount of young workers earn at or around the minimum wage (Del Carpio and Pabon, 2017). Accordingly, adverse employment effects of age-specific policies might be higher than expected (Broecke et al., 2017). Meanwhile, since these countries are usually characterized by high levels of informality and non-compliance with minimum wage, one can also find moderate effects (Broecke et al., 2017). Hence, focusing on the impact of age-specific minimum wages based on a developing country experience, our study will contribute the relatively scant literature.

There are very few studies examining how and to what extent Turkish labor market is affected by the minimum wage policies. Studies examining the existence and direction of minimum wage effects mostly exploit time-series or cross-sectional data [see, e.g., Ozturk (2012)]. Among few, by using the panel structure of HLFS data between 2002 and 2005, Papps (2012) examines employment effects of minimum wage and social security taxes. Using regional level data in HLFS, Pelek (2015) analyzes minimum wage impact on employment of 15-29-year-old individuals in the country during 2004-2014. Besides, very few studies follow a quasi-experimental approach. Employing DID methodology Gurcihan-Yunculer and Yunculer (2016) analyze minimum wage effects on the labor market both at the intensive and extensive margin. Similarly, based on regional variation in the share of minimum wage earners, Bakis et al. (2015) exploit a non-linear DID to estimate the effect of minimum wage on labor market and schooling outcomes of young people in Turkey.

3 Institutional setting: Age-specific minimum wages in Turkey

A significant fraction of workers in Turkey earn at the minimum level. In fact, 35.8% of formal sector workers—i.e., those with social security registration—in private sector and 20.7% of those in public sector are reported as minimum-wage earners to Social Security Institution in 2017. The legal basis of minimum wage in the country consists of Labor Act #4857 and Minimum Wage Regulation. As Labor Act declares, Ministry of Family, Labor, and Social Services (MoFLSS) determines minimum wage at least every two years through Minimum Wage Determination Commission. Whereas the Commission determined minimum wage twice a year during 1997-2015, it annually determines minimum amount of pay since 2016. Moreover, by law, while determining the minimum wage it should consider social and economic conditions of the country, living-condition indices for salaried workers, actual wages, and average living standards.

Workers below age 16 were subject to a lower minimum wage (called the youth minimum wage) than the older workers between 1989 and 2013 in Turkey. Age-specific minimum wage policy aims to facilitate school-to-work transition of young individuals who do not want to pursue higher education. Between 1994 and 2013, the gap between youth and adult rates were more or less stable—workers below age 16 received nearly 15% less than those age 16 and above [Figure (1)]. Note that the minimum legal working age in the country is 15. Therefore, youth minimum wage was effective for age 15 only.

On 31 December 2013, the Minimum Wage Determination Commission abolished the age-specific minimum wage policy and declared a single (adult) minimum wage to be applied to all minimum-wage workers from January 1st, 2014. This change was not anticipated. The issue of equating minimum wages for all workers regardless of age was raised during the meetings, beginning on December 6, 2013 and ending on December 31, 2013. No media debate or discussions were made before. As a consequence of this policy change, the nominal minimum wage applied to 15-year-old workers increased by 20.7% from December 2013 to January 2014. The real minimum wage for workers under age 16 increased by 14.3% in the first half of 2014, while that for workers of age 16 and above did not change. This suggests that the relative increase in real minimum wage of 15-year-old workers might have altered the labor market and educational outcomes of 15-year-old individuals if the change in minimum wage policy is binding for actual wages received.[3]

This policy change significantly increased employers' labor cost in regard to 15-year-old workers employed at the minimum wage. As shown in Figure (2), until 2014, the real cost of minimum-wage workers under age 16 was substantially lower than that of older workers. In fact, between the first half of 2007 and second half of 2013, the real cost of minimum-wage workers under age 16 was, on average, 12.2% lower than the real cost of workers of age 16 and above. Furthermore, in the first half of 2014, the real cost of 15-year-old minimum wage workers increased by 14.1% after the policy change. We use the age-specific minimum wage policy to analyze the impact of minimum wages on employment and educational outcomes of young males in Turkey.

4 Data and empirical approach

4.1 Data description and summary statistics

The primary data source is the 2012-2015 waves of SILC. It is a micro-level longitudinal household survey, which has been annually collected and published by the Turkish Statistical Institute (TurkStat) since 2006. It covers a large set of variables on demography, health, housing, economic conditions, labor markets, social exclusion, asset ownership, and income status (TurkStat, 2017). It has a rotating panel design enabling us to follow an individual over four years. Even though SILC is compiled annually, it includes retrospective information on the monthly main activity of individuals aged 15 years old and over. Furthermore, the monthly main activity compiled in a given year refers to the previous year's information. This means that the 2012-2015 waves of SILC data include information on the main activity of individuals in 2011-2014. Monthly individual activity is of our interest, because it allows us to generate our main outcome variables. Also, SILC contains month of birth and year of birth information for each individual observed. Therefore, we are able to compute "age in months," which is a key object in our empirical

[3]Turkey has a large informal labor market, which means that whether the minimum wage changes are binding on actual wages or not is a relevant concern.

design. We primarily focus on the 2014-2015 waves of this panel survey as we wish to concentrate on the years before and after the policy change (2013 and 2014).

We restrict our sample to young males, because labor force participation behavior of young females might be driven by factors different from those of males in Turkey. Specifically, social, cultural, and religious factors might be more influential than the economic factors in female's labor supply decisions (SPO and the World Bank, 2009). To abstract from this additional complexity, we focus on males and exclude females from our sample.

"The main activity of a respondent" is a separate question for each month in a given year so that each individual of age 15 and above answers a sequence of questions on main activity—from January to December in a given year. Since we use the 2014-2015 panel of SILC, we are able to collect information on main activity per month from January 2013 to December 2014. Answer categories of the main activity questions are coded as follows: (1) wage and salaried employee working full-time; (2) wage and salaried employee working part-time (3) own-account workers working full-time including self-employed, employers, and unpaid family workers; (4) own-account workers working part-time including self-employed, employers, and unpaid family workers; (5) looking for a job; (6) in formal education/apprenticeship; (7) retired, being in early retirement, or quit working; (8) old, disabled, or unable to work; (9) in compulsory military service[4]; (10) taking care of elderly/children/disabled and homemakers; (11) other inactive individuals. These categories are mutually exclusive so that a respondent has to declare the main activity in the relevant month s/he spends most of her/his time doing it. Using these categories, we construct binary outcomes on being employee, employed, unemployed, in labor force, in education, and neither in employment nor in education.

We restrict our model estimations to 15-16-year-old males.[5] This corresponds to a 24-month bandwidth around the cut-off value, 16 years-0 month old age. We cannot include younger individuals, because individuals under 15 are not legally allowed to work in Turkey. Besides, to avoid a probable differential treatment of individuals on both sides of 16-year-old age cut-off, we do not include males above 17.[6] Since numerous employment

[4]We exclude the observations under (9) (in military service), because males doing their compulsory military service are excluded from the non-institutional population of the country.

[5]This corresponds to young males who are aged between 15 years-0 month old and 16 years-11 months old. We mostly stick with this age group throughout the empirical analysis.

[6]Kreiner et al. (2017) point out similar threats to RD setting in their study. They discuss that in Denmark, teenagers

subsidies are available for youth as they turn 18; not only they wish to enter labor market because more job opportunities are available, but also firms demand more workers over 18. Moreover, age 17 might be another cut-off because schooling decision of individuals over 17 would be different from that of the younger ones. Indeed, young persons who are 17 years old and over might consider entering college as an alternative to job market. Yet, the choice of younger people would be entering secondary education versus labor market.

Table (1) presents several characteristics of 15-year-old and 16-year-old males before the policy was introduced in Turkey. As seen, the two groups of males are very similar in many respects. No significant difference in their educational attainment exists. These two groups of males are living in the household of similar sizes. The proportion of those having good health are very close, though this difference is significant at 10% level. On the other hand, 15 year-olds differ from 16 year-olds in terms of job tenure, working hours and real monthly wages. Moreover, share of males being either employee, employed, unemployed, in labor force, or neither in employment nor in education are higher for 16-year-old males in 2013. A fewer proportion of 16-year-old males attend school in the same year. Indeed, these characteristics are outcomes and not determined independently of the age of males.[7]

4.2 Identification strategy

We exploit an RD design to analyze the impact of youth minimum wage policy in Turkey. RD design can be used to evaluate a policy or a program, as long as subjects are treated under the policy/program if their value of a known variable—rating variable—is above or below a predetermined cut-off. Indeed, the differentiation of minimum wage according to age in Turkey provides a quasi-experiment which is applicable to this design.

Let $D_i = D(z_i) = \mathbb{1}(z_i \geq z_0)$, where the rating variable z is the age of a worker and z_0 is the 16 years old age cut-off. Then, an outcome variable, y_i, can take two values based on z: y_{1i} if an individual is able to get the adult rate of minimum wage, i.e., $D_i = 1$, or y_{0i} if he is not. The difference between these two, $y_{1i} - y_{0i}$, gives the impact of this policy (Angrist and Pischke, 2008). However, a person can be either 16 years old and

not only are able to receive higher minimum wages but also become eligible to certain types of welfare benefits as they cross over the age threshold. To eliminate the potential bias, they remove welfare benefit recipients in their analysis.

[7] Table (2) illustrates same statistics for males in 2014.

over, or under it, and he can never be on both sides of 16 years old simultaneously. Therefore, we cannot observe y_{1i} and y_{0i} at the same time to derive this impact (Imbens and Lemieux, 2008).Yet, the RD design enables us to evaluate this effect by comparing average outcomes of the persons who are just below and just above this age.

Under continuity and certain smoothness conditions in the close vicinity of 16 years of age cut-off, average effects of the youth minimum wage policy can be obtained by differing left and right limits of the conditional expectation function (CEF). More formally, Equation (1) gives the effect of this policy (Hahn et al., 2001):

$$\lim_{z \searrow z_0} \mathbb{E}[y_i|z] - \lim_{z \nearrow z_0} \mathbb{E}[y_i|z] = \mathbb{E}[y_{1i} - y_{0i}|z = z_0] = \mathbb{E}[\beta_i|z = z_0]. \tag{1}$$

Based on continuity, $\mathbb{E}[y_{1i}|z = z_0 - \varepsilon]$ can be regarded as a counterfactual for $\mathbb{E}[y_{1i}|z = z_0]$, for arbitrarily small $\varepsilon > 0$. However, our rating variable age is available in months which might violate the continuity condition on potential outcomes (Calonico et al., 2014). In fact, we might not compare local averages at $z = z_0$ and $z = z_0 - \varepsilon$, because we do not observe outcomes for all small $\varepsilon > 0$. However, in their influential work, Lee and Card (2008) argue that RD inference can still be possible even with a discrete rating.[8] In the case of a discrete rating, we can identify $E[\beta_i|z = z_0]$ by Equation (2):

$$y_i = \alpha + \beta D_i + f(z_i) + \eta_i \tag{2}$$

where $u_i = f(z_i) + \eta_i$ and $f(\cdot)$ is a continuous link function such that $f(0) = \mathbb{E}[y_0|z = z_0]$. By approximating this function with a first order polynomial[9], Equation (2) becomes

$$y_i = \alpha + \beta D_i + \gamma(z_i - z_0) + a_i + \eta_i. \tag{3}$$

Here, $a_i \equiv f(z_i) - \gamma(z_i - z_0)$ is the specification bias which measures the deviation of $f(\cdot)$ from true CEF. It is also assumed to be random with $\mathbb{E}[a_i|z = z_i] = 0$.[10] Since the specification bias is viewed as a random error, there exist a within-group correlation in η. To account for this correlation, error terms should be adjusted to have consistent estimates for β. Indeed, if we assume the equality of random errors in each side of the cut off, clustered standard errors will be valid for inference (Lee and Card, 2008).

[8] They propose a parametric approach because local linear regression cannot assign any weight to the observations on $z_0 - \varepsilon$ for very small ε due to lack of continuous data. However, later research reveals that non-parametric approach can be also used [e.g. Calonico et al. (2014)]. Still, we follow a parametric approach in the estimation of our models.

[9] Higher order polynomials are also possible. The idea, however, remains the same.

[10] Lee and Card (2008) point out that orthogonality of a_i and z_i might not be always easy to satisfy. However, the classical approach requires no specification error, which is a condition that is more restrictive.

Letting different trends in both sides of the cut-off, the first model we construct within the conventional RD design is given by

$$y_i = \beta_1 D_i + \beta_2 (z_i - z_0) + \beta_3 D_i \cdot (z_i - z_0) + u_i, \tag{4}$$

where y_i is a binary outcome variable on the labor market and schooling, D_i is the dummy for individuals older than 16 years old, and $z_i - z_0$ is the age in months relative to 16th birthday. Following Gelman and Imbens (2018), we allow for a first order polynomial link between outcome and rating variables. Additional covariates are not used because (i) except for age and main activity, no other variable is available on a monthly basis in data, (ii) variables like labor market experience, occupation etc. are not exogenous to the main activity of teenagers, so that even if data were available, it would not be meaningful to include any, and (iii) inclusion of other explanatory covariates are not necessary to identify unbiased or consistent estimates in RD design (Angrist and Pischke, 2008).

4.3 Visual evidence

We start with presenting suggestive visual evidence before providing estimation results. First, we analyze how outcome variables evolve with age to observe size and direction of the jump at the cut-off value. Figure (3) presents evolution of mean values of each outcome plotted against age in months for 15-16-year-old males in 2013. In this year, individuals became entitled to get a higher minimum wage as they turn 16 because the policy did not come into effect. Hence, any jump at this threshold can be evaluated as treatment effect in a conventional RD setting. Figure (3) presents strong evidence that minimum pay based on the age cut-off reduces employment probabilities for young males. Indeed, the discontinuity at 16 years old age cut-off is -1 pp (Panel A) for employee outcome and -2 pp (Panel B) for employed outcome. In other words, the probability of being employee, for instance, is lowered by 1 pp at 16 years old for males. We also observe negative effects for labor force participation (Panel D), but positive effects for unemployment (Panel C), education (Panel E), and being neither in employment nor in education (Panel F) outcomes.

Secondly, we discuss the extent to which minimum wage is binding as informal working is widespread among 15-16-year-old males in Turkey. According to HLFS[11], 90.5% of 15-

[11] Here, we use HLFS data because SILC does not include wages on a monthly basis, but HLFS does. It collects net monthly wages, together with the age (available in years) of the respondent.

year-old and 84.2% of 16-year-old males were working without social security in 2013.[12] Yet, a significant portion of the young males are earning at or around the minimum wage. During 2009-2013, 7.6% of 15-year-old males and 9.1% of 16-year-old males were paid exactly at minimum wage level.[13] Besides, these ratios increased to 14.7% and 18.4% for 15-year-old and 16-year-old males, respectively, in 2014. To have a better sense about whether minimum wage is relevant for the young males, we estimate Kernel density of real wages for both 15-year-old and 16-year-old males. Kernel density estimates are commonly used in empirical literature because they depict unconditional wage distributions, thereby showing the spikes if there exists any (see, for example, Pereira (2003); Portugal and Cardoso (2006); Rani et al. (2013)). Indeed, if there are spikes in a wage distribution at and around the minimum wage, then it might be regarded as binding[14] Rani et al. (2013). Figure (4) and Figure (5) present Kernel density estimates of log of real wage distributions for young males in 2013 and 2014. The dashed lines in these figures correspond to the log of the real minimum wages in each year.[15] Visual inspection of these figures suggests that young male workers in Turkey are concentrated at or around the real minimum wages in both years. This can be viewed as a signal of a binding minimum wage for 15-year-old and 16-year-old male workers. Figure (4) also shows that after the increase in minimum wage of 15-year-old males, their density around the minimum wage's new level increased in 2014. It indicates that the elimination of age-based differential in the minimum wage improved the wage distribution of 15-year-old males. Besides, Figure (5) shows that the density of 16-year-old male workers at the minimum wage also increased prominently in 2014.

5 Results and discussion

In this section, we document empirical results of the model presented in previous section.[16] We start with the impact on labor market outcomes of the youth minimum wage policy,

[12] Monthly individual activity mutually excludes workers and students in SILC data. So, to provide a consistent analysis, we do not include workers who are continuing to education in this part.

[13] Due to possible measurement, rounding and recall errors in HLFS data, we use 5% bandwidth around the minimum wage.

[14] Rani et al. (2013) point out that there can be other reasons creating spikes in the wage distributions such as the presence of wages specific to some occupations. Yet, Kernel density estimates are useful in showing the whole wage distribution and the density around the minimum wage.

[15] Since the minimum wage is set biannually in Turkey, we take the averages of minimum wages for each group in each year to avoid complication in the figures.

[16] Before estimating the RD model, we examine discontinuity of the rating density at cut-off value as a way of testing manipulation. Based on the density test developed by Cattaneo et al. (2015), we do not reject the null hypothesis of manipulation. Figure (6) also shows the estimated density plot of the age of males in 2013.

then, move to the results of educational effects. Table (3) presents empirical results of the estimation of Equation (4). This equation is estimated for 15-16-year-old males in 2013. In regression estimates, we include quarterly calendar time and month of birth dummies as controls. We apply local linear regression and optimally compute mean-squared error (MSE) and coverage error-rate (CER) optimal bandwidths following the algorithm developed by Calonico et al. (2017). We also present robustness of our results by parametric regression estimates using six months and one-year bandwidth around the cut-off [see Table (3)]. While the former consists of males aged between 15 years and 6 months old and 16 years and 6 months old; the latter includes 15-16-year-old males.

5.1 Labor market outcomes

Employment. Table (3) shows that increase in minimum wage as males turn 16 reduces the probability of being employed[17] in Turkey. The reduction in this probability is between 2 and 4 pp for salaried workers, and between 3 and 5 pp for employment in any type. Notwithstanding high levels of informality, this is not a surprising result. In fact, negative employment effects among young workers are often found in developing economies (Broecke et al., 2015). Earning at or around the minimum amount of pay, young workers are more vulnerable to changes in the minimum wages.

Our findings are in line with the results obtained by Kabatek (2015), Kreiner et al. (2017) and Fidrmuc and Tena (2018). Similarly, Papps (2012) and Bakis et al. (2015) report negative employment effects of the minimum wage for broader youth population in Turkey. Pelek (2015) finds that increases in minimum wage deteriorates only informal wage employment of 15-29-year-old individuals while detecting no significant effects on formal wage employment. However, use of regional variation in Kaitz index in that study might be misleading. Because minimum wage is set at the national level and regional Kaitz index represents average wage differences across regions; minimum wage variable in each region can be correlated with the employment rates.

Labor force participation. Table (3) illustrates that increase in minimum wage does not significantly affect labor force participation of young males in Turkey. Estimated coefficients are significantly negative only when we use one-year bandwidth. There are

[17] This result is regardless of being at paid work or employed in any type.

very few studies among the scant literature on labor force participation effects of youth minimum wage [e.g. Fidrmuc and Tena (2018), Marimpi and Koning (2018)]. In particular, only very few are on Turkey. Bakis et al. (2015) find negative effects of the minimum wage on the participation of 15-19 years old young individuals in the country. Similar to ours, Dickens et al. (2014) do not find a significant discontinuity on the inactivity rates of males around 22-year-old age cutoff.

Unemployment. We finally investigate unemployment outcome regarding labor market impact of youth minimum pay policy. Table (3) shows that probability of being unemployed increases among young males with the increase in minimum wage based on the age cut off in 2013. This impact is around 2 pp. Our findings regarding unemployment effects are in line with the expectations of two-sector model, suggesting that the hope of getting higher wages would create a queue for the formal jobs, and hence unemployment, which might persist Mincer (1976). However, we do not observe that this is the correct way of interpreting our results. This is because even if both formal and informal sectors are available for young males, a significant proportion of 15-16 year-old males are located in the latter one. This is why when young males are laid off due to higher minimum pay, they probably become unemployed and look for informal jobs, not queue up for the formal ones. In fact, according to HLFS, 78.5% of 15 year-old males search for jobs as 'service or sales worker' or jobs 'in elementary occupations,' almost all of which are informal in 2014.

5.2 Educational outcomes

Education. Findings on the labor market outcomes imply that a higher minimum wage reduces employment chances of young males in Turkey. When young people aged 15-16 years old expect a decline in job opportunities, enrolling school can be an option for them. Human capital theory predicts that minimum wages might discourage young people from attending school through an increase in the foregone earnings, i.e., opportunity cost of education. Nonetheless, this is conditional on employment opportunities in the market. If high levels of minimum wage lowers the chances of young individuals in getting a job, then the cost of foregone work will decline instead. As this happens, minimum wage encourages young people attending school.

Table (3) reports that higher minimum wage improves school participation of young males in the country. Indeed, education participation increases by 1-2 pp with a higher minimum wage applied to youth. This is of importance because exiting to school in response to the change in youth minimum wage policy might increase labor market efficiencies in future through more skilled labor. Our findings are similar to those obtained by Bakis et al. (2015) providing positive effects on the schooling of 15-19-year-old males in Turkey.

Neither in employment nor in education. Table (3) shows that a higher minimum wage increases the probability of young males being neither in employment nor in education in Turkey. This impact is around 2-3 pp. Neumark and Wascher (1995a) and Neumark and Wascher (1995b) provides similar findings based on US evidence. The significant effects on this outcome signal a threat to the policy impact. It is because if the displaced young males due to the policy place themselves out of education, then pushing them to a state in which they can be productive will require some costs. Besides, psycho-social problems associated with being out of employment and education might be costly for the country as a whole. In fact, young individuals who are neither in employment nor in education are more likely to be involved in crime and/or violence than their active counterparts (Henderson et al., 2017).

5.3 Robustness checks

Difference-in-discontinuities. Within the conventional RD model, we are able to analyze policy effects as long as it only depends on the ratings of a single variable. In our case, this variable is the age in months of an individual. When age is defined in a monthly scale, there might be some unobserved confounding factors such as ability differentials pertaining to certain age groups (in months), thereby contaminating the policy effect. Indeed, such confounding might generate another jump at the threshold value. This would then interrupt the usual RD design. Nonetheless, taking before/after difference of the policy change in 2014, January allows us to remove such contamination. By comparing the discontinuity before and after this policy change might yield the effects of the rise in minimum wage for males younger than 16 years old in Turkey. This design is like a combination of RD with DID. Borrowing from Grembi et al. (2016), we call it as "difference-in-discontinuities" ("diff-in-disc" in short) approach.

Within the diff-in-disc framework, y_i can take four values. It can be either y_{1i}, post (when $T_i = 1$, and Post $= 1$, where T is the treatment dummy for being younger than 16 years old and Post is the post treatment dummy), y_{0i}, post (when $T_i = 0$, and Post $= 1$), y_{1i}, pre (when $T_i = 1$, and Post $= 0$) or y_{0i}, pre (when $T_i = 0$, and Post $= 0$). Then, letting $\mu^-_{\text{pre}} = \mathbb{E}[y_{0i}|z_i = z_0, t \leq t_0]$, $\mu^+_{\text{pre}} = \mathbb{E}[y_{1i}|z_i = z_0, t \leq t_0]$, $\mu^-_{\text{post}} = \mathbb{E}[y_{0i}|z_i = z_0, t \geq t_0]$, and $\mu^+_{\text{post}} = \mathbb{E}[y_{1i}|z_i = z_0, t \geq t_0]$, Grembi et al. (2016) show that $\hat{\tau}_{DD}$ (Equation (5)) is the diff-in-disc estimator for the treatment effect:

$$\hat{\tau}_{DD} = (\mu^+_{\text{post}} - \mu^-_{\text{post}}) - (\mu^+_{\text{pre}} - \mu^-_{\text{pre}}). \tag{5}$$

Based on this, we estimate the following equation under diff-in-disc framework:

$$y_i = \beta_1 D_i + \beta_2(z_i - z_0) + \beta_3 T_i \cdot (z_i - z_0) + \alpha_1 \cdot \text{Post} + \alpha_2 T_i \cdot \text{Post} + u_i. \tag{6}$$

Estimation results of Equation (5) within diff-in-disc design are reported in Table (4). These are similar to the results we obtain from standard RD regression estimates. Table (4) shows that when 15-year-old young males become entitled to a higher minimum pay after the policy change in 2014, their chances in finding a job decline [Table (4)]. The change in probability of being employed as salaried worker for males under 16 is between 1-3 pp less than the older males, after the policy change. This change is between 3-6 pp for the employment probability in any type. Prior to change in minimum pay policy in January 2014, 15-year-old workers were 14.2% cheaper on average to employers, compared to their 16-year-old counterparts in 2013. This provided an advantage for younger workers in terms of getting a job when competing with a candidate from older age group because their lower cost might compensate for the productivity differentials. When the policy was introduced, they lost their labor cost advantage. This makes the employers to follow a job hiring process which is now not in favor of the 15-year-old workers. Indeed, as the cost advantage of 15-year-old males are eliminated, their chances in getting a job relative to 16-year-old workers decline, thereby making employers to substitute some of them for 16-year-old males. Our findings on the employment effects are in line with the results obtained by Pereira (2003), Yannelis (2014), Kreiner et al. (2017) and Shannon (2011). Shannon (2011) shows that abolition of youth minimum wage rates in seven provinces of Canada reduces employment status of 15-16-year-old workers is by 2-3.5 pp. According to Table (4), change in the probability of 15-year-old males being in labor force is 1-3 pp less compared to 16-year-old males after the removal of age-specific minimum wage policy. We might infer that decline in the quantity of young labor demanded in response to increase in labor cost discourages them from looking for a job in the labor market. Similar to RD estimation results, this policy aggravates unemployment outcomes of young males. Results of diff-in-disc specification implies that change in the probability of being unemployed is 2-3 pp more for 15-year-old males than that of 16 year-old males [Table (4)]. Impact of youth minimum wage policy on education outcomes based on diff-in-disc estimates are also in line with those obtained from the standard RD estimates. Table (4) shows that relative to 16 year-old males, change in the probability of 15 year-old males being in education is 1-3 pp more after the policy introduced in January 2014. Besides, the change in the probability of 15 year-old males who are neither in employment nor in education are 2-4 pp less after the policy change compared to 16 year-old males [Table (4)].

Discreteness of the rating variable. Within the RD models, we employ age as the rating variable, which we observe monthly in our data set. Since age is not truly continuous, we cluster the standard errors following the methodology proposed by Lee and Card (2008). Although it is a frequently used approach by the empirical world, clustering of standard errors to ensure accuracy are sometimes subjected to criticism. For instance, Kolesar and Rothe (2018) argue that specification bias might not be random as assumed by Lee and Card (2008), because many data are created using i.i.d. sampling from a fixed population.

In this part, we consider whether we should regard age in months as a true discrete rating. Point is that within an RD setting like ours, a rating variable, which is not truly continuous, can sometimes be regarded as if it is not. In fact, if distance among support points are not wide near cut-off value, estimation bias of treatment effect due to discreteness of the rating might be ignorable. On the other hand, if these gaps were not sufficiently narrow, then estimation bias would not asymptotically converge to zero, and non-clustered standard errors might be more appropriate in that case. (Kolesar and Rothe, 2018).

Because our rating variable is age, we deal with the issue resulting from measuring age in different scales. Many studies utilizing RD as a quasi-experimental design use age as rating variable (e.g., Lalive (2008)). Its widespread usage is because age is a variable that cannot easily be manipulated—a property required for a valid RD inference. On the other hand, studies usually utilize it in different scales, mostly due to the nature of data. Indeed, some studies employ age in years (e.g., Oreopoulos (2006)), some use age in months (e.g., Lalive (2008)) and some others use age in a narrower scale (e.g., Dickens et al. (2014)). We conjecture that exploiting different scales of age would not make any significant difference in our study. It is because age variable shows almost uniform distribution regardless of the scale we choose. Even though SILC data contains age in a monthly scale, another data source can guide us. Specifically, we exploit administrative records of Turkish Employment Agency[18] and plot histogram of males (*i*) born in the same week of a month in a year, (*ii*) born in the same month of a year, (*iii*) born in the same year for 17-18 years old males.[19] Figure (7) illustrates the histogram of males born in the third week of February 1990—18-year olds at the registration date. As seen, it represents almost a uniform distribution for weekly data. Moreover, the shape of age distributions would almost remain same if we take either a monthly [Figure (8)] or a yearly [Figure (9)] interval.[20] Hence, uniformity of age distributions might imply that using age in a weekly, a monthly or a yearly scale would not make any significant difference in our estimations. Besides, using a very similar experiment within RD setting, Dickens et al. (2014) show that using weekly, monthly or 6-week bin widths in estimating the effects of minimum wage does not change their results.

Results after the abolishment of age-specific minimum wage. We consider the possibility that impact of the age-specific rule on minimum wage might be due to an artifact of data or caused by factors other than the minimum wage policy. Thence, we re-estimate Equation (4) for the same age group of males in the country after the abolishment of age-specific policy in January 2014.[21] Since the same minimum wage applies to all workers regardless of the age, we do not expect any discontinuity during

[18] Turkish Employment Agency is the main authority responsible for matching services and active labor market policies in Turkey. The latest data available to us covers all unemployed registered to the Agency in April 2008 with their birth dates.

[19] Instead of 15-16 years old males, we consider 17-18 years olds because there are fewer number of observations for the younger group.

[20] Distribution of males born in January is relatively different because parents do not usually prefer to register their kids if he/she born in the last month of year, thereby postponing their registration to the first day of the following year. Hence, we observe empty support in the last days of a year and an accumulation in first day. For instance, only about 20% of males born in December 1990, born in the last ten days of this month. However, using a bin size narrower than one month would not solve this problem because some support points become empty in such case. Besides, since we take before/after difference in diff-in-disc model, this kind of accumulation is removed in regression estimates.

[21] Minimum wage policy has been applied since 1951. But, we use data for the post reform period because no data was available prior to 1951.

the post-policy period. To replicate our estimates, we use 2014-2017 SILC data, and restrict our sample for the years 2016 and 2017. Main activity of individuals in this sample corresponds to 2015 and 2016, respectively. We exclude 2014 from our sample because we believe that employers react to the policy by adjusting the composition of the workers they employ just after the reform. The local linear estimation of Equation (4) with this sample are reported in Table (5). We do not observe any significant change at 16-year-old age cut-off in terms of both labor market and education outcomes after the abolishment of the age-specific minimum wage rule in the country.

2012 education reform. In 2012, the compulsory schooling system was changed with the Law #6287. Prior to the reform, eight years continuous education was mandatory. By this reform, twelve years—4 years for each of primary, elementary and high school—were enforced beginning in September 2012. This can contaminate our results as long as it creates a significant jump in the high school enrollment of males affected by the policy change. However, Tumen (2018) shows that weaknesses in the enforcement mechanisms hinders the implementation of the reform. He finds that even though the Law forces individuals to enroll in school, it does not create a jump in the high school enrollment ratios both for males and females. When we analyze 15-16-year-old males in a similar manner, high school enrollment rates of this age group does not also show any significant jump in 2012 as well [Figure (10)].

Clustering standard errors. Independent of the research design, clustering of standard errors is a way of adjustment often used in empirical world as long as observations within the same cluster are believed to have unobserved characteristics that are correlated. And, males born in the same month of a given year might share some common, but unobserved, characteristics. Then, clustering for age in months makes sense to our regression estimates. However, one potential problem might be the number of clusters. In fact, we have relatively few clusters—24 in each regression estimate. Because asymptotic approximations for clustered standard errors require large numbers of clusters, using 24 clusters as in our study might lead to invalid inference (Angrist and Pischke, 2008). On the other, as Cameron and Miller (2015) list, there are several ways to adjust standard errors when few clusters are available. This is why we run our regressions with the standard errors corrected by the Moulton (1986) factor as well [Table (6)]. Still, these findings produce similar results with those obtained when clustered standard errors are not corrected.

6 Concluding remarks

In this paper, we estimate the impact of youth minimum wage policy on labor market and education outcomes of 15-16-year-old males in Turkey. High degrees of informality and non-compliance to law together with high shares of minimum wages earners complicate answering this question like in many developing countries. Despite the mystery, the impact of minimum wages is less well studied in these economies. In Turkey, workers under 16 were entitled to receive the youth rate of minimum wage prior to 1 January 2014. This age-specific rule created 15% difference between the youth and adult rate. Minimum Wage Determination Commission abruptly eliminates the rule after that date. We design a quasi-experimental setup by using age-specific minimum wage policy in the country.

We find that youth minimum wage policy in Turkey reduces employment of young males. Besides, it increases unemployment and school enrollment of them. We can infer that the elimination of labor cost advantage of males receiving youth rate before the policy change generates a substitution among the young males. The compositional shift following the change in minimum wage might underpin why some studies fail to detect significant aggregate employment effects. This result also suggests that increase in the youth minimum wage reduces the quantity of young labor demanded that fits the conventional wisdom in minimum wage economics. Reduction in employment probabilities yet does not tell the whole story. Other labor market and education outcomes are worth dealing with. Our results suggest that some of the displaced young males either become unemployed in the hope of getting a higher paying job or enroll school. Taken at face value, it implies that the removal of youth minimum wage will contribute school enrollment rates of young males in Turkey. This is desirable and consistent with the country's education policy, which extended the compulsory schooling years in 2012. On the other hand, the change in youth minimum wage policy created adverse impact on the young males who were neither in employment nor in education. This would harm the policy impact because if the displaced young workers place themselves out of education, then pushing them to a state in which they can be more productive will require some economic and social costs.

References

Acemoglu, D. (2001): "Good Jobs versus Bad Jobs," *Journal of Labor Economics*, 19, 1–22.

Allegretto, S. A., A. Dube, and M. Reich (2011): "Do Minimum Wages Really Reduce Teen Employment? Accounting for Heterogeneity and Selectivity in State Panel Data," *Industrial Relations*, 50, 205–240.

Angrist, J. D. and J.-S. Pischke (2008): *Mostly Harmless Econometrics: An Empiricist's Companion*, Princeton, NJ: Princeton University Press.

Bakis, O., M. Hisarciklilar, and A. Filiztekin (2015): "The Impact of a Minimum-Wage Increase on Employment and School Enrollment: Evidence from Turkey," Koc University EAF Conference Paper.

Belman, D. and P. J. Wolfson (2014): *What Does the Minimum Wage Do?*, WE Upjohn Institute.

Boeri, T., P. Garibaldi, and M. Ribero (2011): "The Lighthouse Effect and Beyond," *Review of Income and Wealth*, 57, 54–78.

Broecke, S., A. Forti, and M. Vandeweyer (2015): "The Effects of Minimum Wages on Employment in Emerging Economies: A Literature Review," Social, Employment and Migration Working Papers.

——— (2017): "The Effect of Minimum Wages on Employment in Emerging Economies: A Survey and Meta-Analysis," *Oxford Development Studies*, 45, 366–391.

Calonico, S., M. D. Cattaneo, M. H. Farrell, and R. Titiunik (2017): "rdrobust: Software for Regression Discontinuity Designs," *The Stata Journal*, 17, 372–404.

Calonico, S., M. D. Cattaneo, and R. Titiunik (2014): "Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs," *Econometrica*, 82, 2295–2326.

Cameron, A. C. and D. L. Miller (2015): "A Practitioner's Guide to Cluster-robust Inference," *Journal of Human Resources*, 50, 317–372.

Campolieti, M., T. Fang, and M. Gunderson (2005): "How Minimum Wages Affect Schooling-Employment Outcomes in Canada, 1993–1999," *Journal of Labor Research*, 26, 533–545.

Cattaneo, M. D., M. Jansson, and X. Ma (2015): "rddensity: Manipulation Testing in Stata," *Stata Journal*, 1–18.

Crofton, S. O., W. L. Anderson, and E. C. Rawe (2009): "Do Higher Real Minimum Wages Lead to More High School Dropouts? Evidence from Maryland Across Races, 1993–2004," *American Journal of Economics and Sociology*, 68, 445–464.

Del Carpio, X. V. and L. M. Pabon (2017): "Implications of Minimum Wage Increases on Labor Market Dynamics Lessons for Emerging Economies," World Bank Policy Research Working Paper #8030.

Dickens, R., R. Riley, and D. Wilkinson (2014): "The UK Minimum Wage at 22 Years of Age: A Regression Discontinuity Approach," *Journal of the Royal Statistical Society: Series A*, 177, 95–114.

Fidrmuc, J. and J. D. D. Tena (2018): "UK National Minimum Wage and Labor Market Outcomes of Young Workers," *Economics E-Journal*, 12, 1–28.

Fiszbein, A. (1992): "Do Workers in the Informal Sector Benefit from the Cuts in the Minimum Wage?" *Policy Research Working Paper Series No. 826.*

Gelman, A. and G. Imbens (2018): "Why Higher Order Polynomials Should not be Used in Regression Discontinuity Designs," *American Statistical Association.*

Gorry, A. (2013): "Minimum Wages and Youth Employment," *European Economic Review*, 64, 57–75.

Grembi, V., T. Nannicini, and U. Troiano (2016): "Do Fiscal Rules Matter?" *American Economic Journal: Applied Economics*, 8, 1–30.

Gurcihan-Yunculer, H. B. and C. Yunculer (2016): "Minimum Wage Effects on Labor Market Outcomes in Turkey," Central Bank of the Republic of Turkey, Working Paper #16/14.

Hahn, J., P. Todd, and W. van der Klaauw (2001): "Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design," *Econometrica*, 69, 201–209.

Henderson, J. L., L. D. Hawke, G. Chaim, and N. Y. S. P. Network (2017): "Not in Employment, Education or Training: Mental Health, Substance Use, and Disengagement in a Multi-sectoral Sample of Service-seeking Canadian Youth," *Children and Youth Services Review*, 75, 138–145.

Hyslop, D. and S. Stillman (2007): "Youth Minimum Wage Reform and the Labour Market in New Zealand," *Labour Economics*, 14, 201–230.

Imbens, G. W. and T. Lemieux (2008): "Regression Discontinuity Designs: A Guide to Practice," *Journal of Econometrics*, 142, 615–635.

Kabatek, J. (2015): "Happy Birthday, You're Fired! The Effects of Age-Dependent Minimum Wage on Youth Employment Flows in the Netherlands," IZA Discussion Paper #9528.

Kolesar, M. and C. Rothe (2018): "Inference in Regression Discontinuity Designs with a Discrete Running Variable," *American Economic Review*, 108, 2277–2304.

Kreiner, C. T., D. Reck, and P. E. Skov (2017): "Do Lower Minimum Wages for Young Workers Raise Their Employment? Evidence from a Danish Discontinuity." Forthcoming, *Review of Economics and Statistics.*

Lalive, R. (2008): "How Do Extended Benefits Affect Unemployment Duration? A Regression Discontinuity Approach," *Journal of Econometrics*, 142, 785–806.

Lee, D. S. and D. Card (2008): "Regression Discontinuity Inference with Specification Error," *Journal of Econometrics*, 142, 655–674.

Lemos, S. (2009): "Minimum Wage Effects in a Developing Country," *Labour Economics*, 16, 224–237.

Liu, S., H. T. J. and K. Regmi (2016): "Impact of Minimum Wage on Youth Labor Markets," *Labour*, 30, 18–37.

Marimpi, M. and P. Koning (2018): "Youth Minimum Wages and Youth Employment," *IZA Journal of Labor Policy*, 7, 1–18.

Mincer, J. (1976): "Unemployment Effects of Minimum Wages," *Journal of Political Economy*, 84.

Moulton, B. R. (1986): "Random Group Effects and the Precision of Regression Estimates," *Journal of Econometrics*, 32, 385–397.

Neumark, D. and W. Wascher (1995a): "The Effects of Minimum Wages on Teenage Employment and Enrollment: Evidence from Matched CPS Surveys," NBER Working Paper #5092.

——— (1995b): "Minimum Wage Effects on Employment and School Enrollment," *Journal of Business and Economic Statistics*, 13, 199–206.

——— (1995c): "Minimum-Wage Effects on School and Work Transitions of Teenagers," *American Economic Review*, 85, 244–249.

——— (2003): "Minimum Wages and Skill Acquisition: Another Look at Schooling Effects," *Economics of Education Review*, 22, 1–10.

Neumark, D., S. J. M. I. and W. Wascher (2014): "Revisiting the Minimum Wage-Employment Debate: Throwing out the Baby with the Bathwater?" *Industrial and Labor Relations Review*, 67(Supplement), 608–648.

Olssen, A. (2011): "The Short Run Effects of Age Based Youth Minimum Wages in Australia: A Regression Discontinuity Approach," Paper Presented at New Zealand Association of Economists Annual Conference, Wellington, 29 June-1 July 2011.

Oreopoulos, P. (2006): "Estimating Average and Local Average Treatment Effects of Education When Compulsory Schooling Laws Really Matter," *American Economic Review*, 96, 152–175.

Ozturk, O. D. (2012): "Employment Effects of Minimum Wages in Inflexible Labor Markets," Unpublished manuscript, University of South Carolina.

Pacheco, G. A. and A. A. Cruickshank (2007): "Minimum Wage Effects on Educational Enrollments in New Zealand," *Economics of Education Review*, 26, 574–587.

Papps, K. L. (2012): "The Effects of Social Security Taxes and Minimum Wages on Employment: Evidence from Turkey," *Industrial and Labor Relations Review*, 65, 686–707.

Pelek, S. (2015): "The Employment Effect of the Minimum Wage: An Empirical Analysis from Turkey," *Ekonomi-tek*, 4, 49–68.

Pereira, S. C. (2003): "The Impact of Minimum Wages on Youth Employment in Portugal," *European Economic Review*, 47, 229–244.

Portugal, P. and A. R. Cardoso (2006): "Disentangling the Minimum Wage Puzzle: An Analysis of Worker Accessions and Separations," *Journal of the European Economic Association*, 4, 988–1013.

Rani, U., P. Belser, M. Oelz, and S. Ranjbar (2013): "Minimum Wage Coverage and Compliance in Developing Countries," *International Labour Review*, 152, 381–410.

Sen, A., R. K. and C. V. D. Waal (2011): "Teen Employment, Poverty, and the Minimum Wage: Evidence from Canada," *Labour Economics*, 18, 36–47.

Shannon, M. (2011): "The Employment Effects of Lower Minimum Wage Rates for Young Workers: Canadian Evidence," *Industrial Relations*, 50, 629–655.

SPO and the World Bank (2009): "Female Labor Force Participation in Turkey: Trends, Determinants, and Policy Framework," Turkish State Planning Organization and the World Bank: Washington, DC.

Tumen, S. (2018): "The Impact of Low-Skill Refugees on Youth Education," IZA Discussion Paper #11869.

TurkStat (2017): "The Survey of Income and Living Conditions Methodological Explanation," http://www.tuik.gov.tr/PreHaberBultenleri.do?id=24579.

Yannelis, C. (2014): "The Minimum Wage and Employment Dynamics: Evidence from an Age Based Reform in Greece," University of Chicago, Unpublished Manuscript.

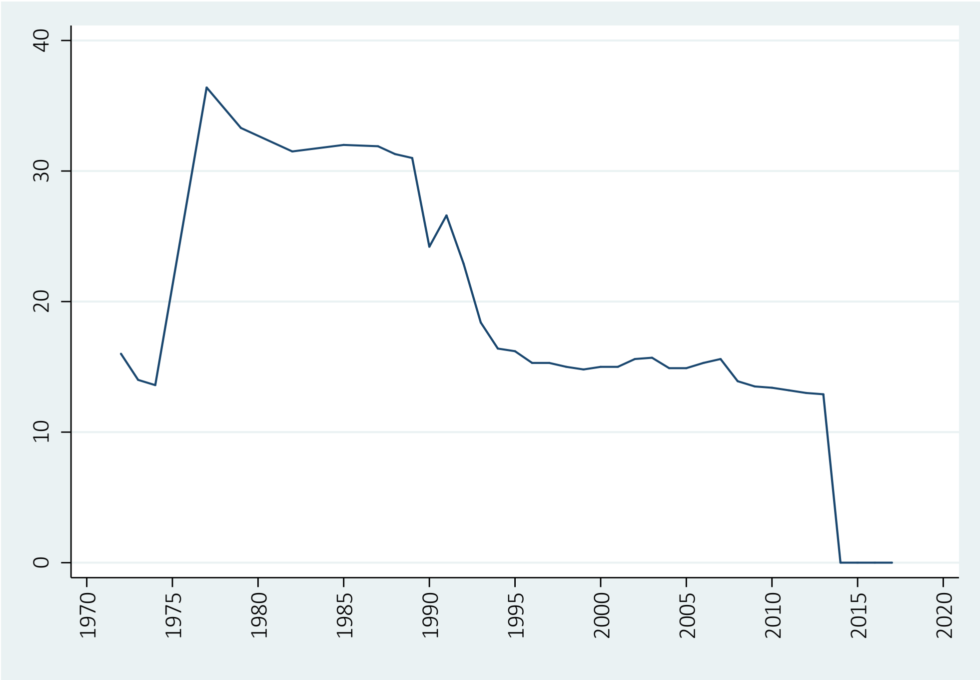

Figure 1: Gap between youth and adult minimum wages in Turkey. (1972-2017, percent of adult minimum wage.) *Data Source:* Minimum Wage Determination Commission (1972-1995), and Ministry of Family, Labor, and Social Services (1996-2017).

Figure 2: Real cost of minimum wage by age. (From the first half of 2007 to the end of the second half of 2015.) *Source:* Ministry of Family, Labor, and Social Services. PPI is used to deflate the nominal figures (2007 is the base year).

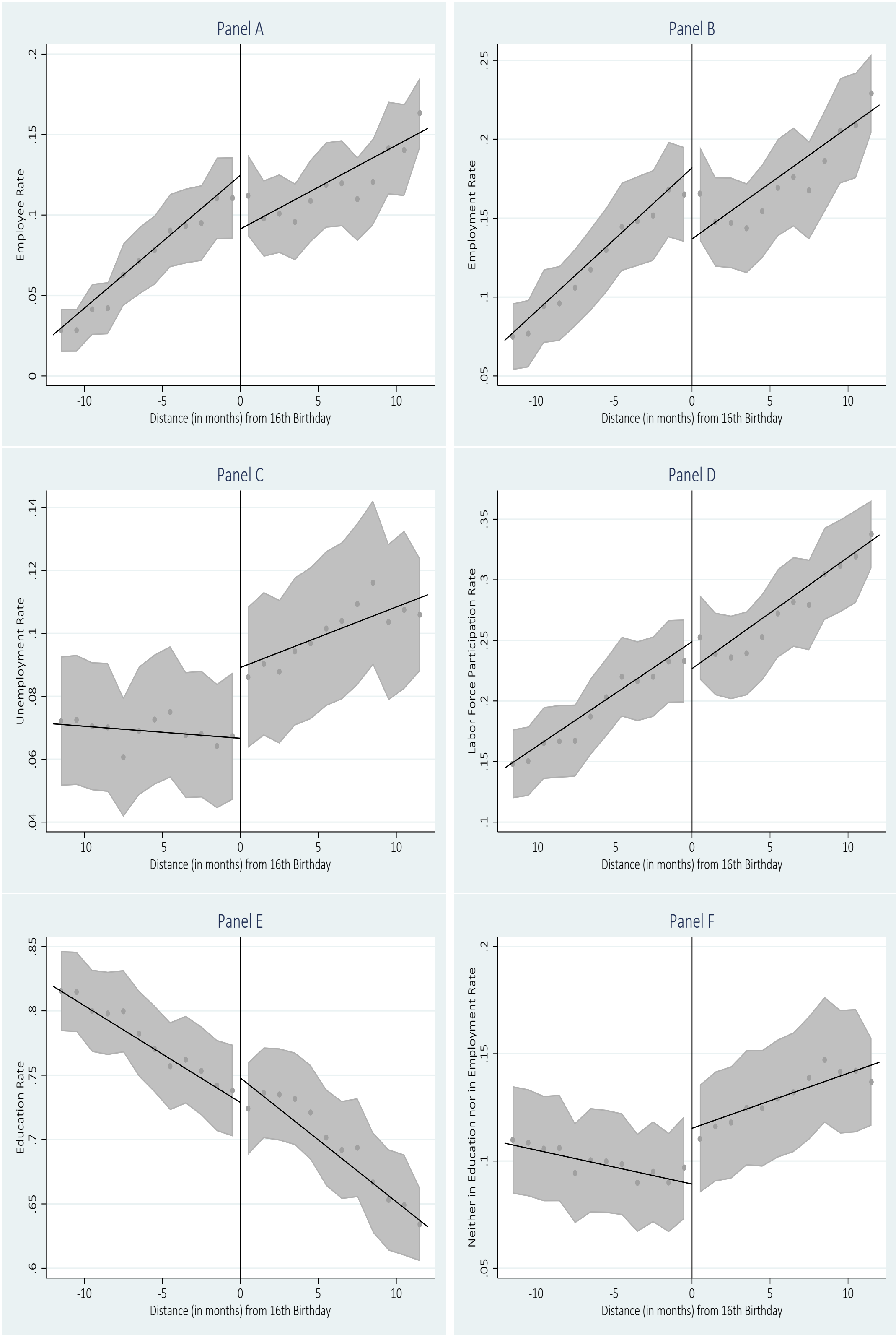

Figure 3: Averages of Labor Market and Schooling Outcomes for Males (2013). *Source:* Own calculations using SILC. *Notes:* Age in months is centered at 16 years old, implying that any point on each side represents the distance to 16 years old threshold (e.g., -5 corresponds to the observations who are 15 years and 7 months old).

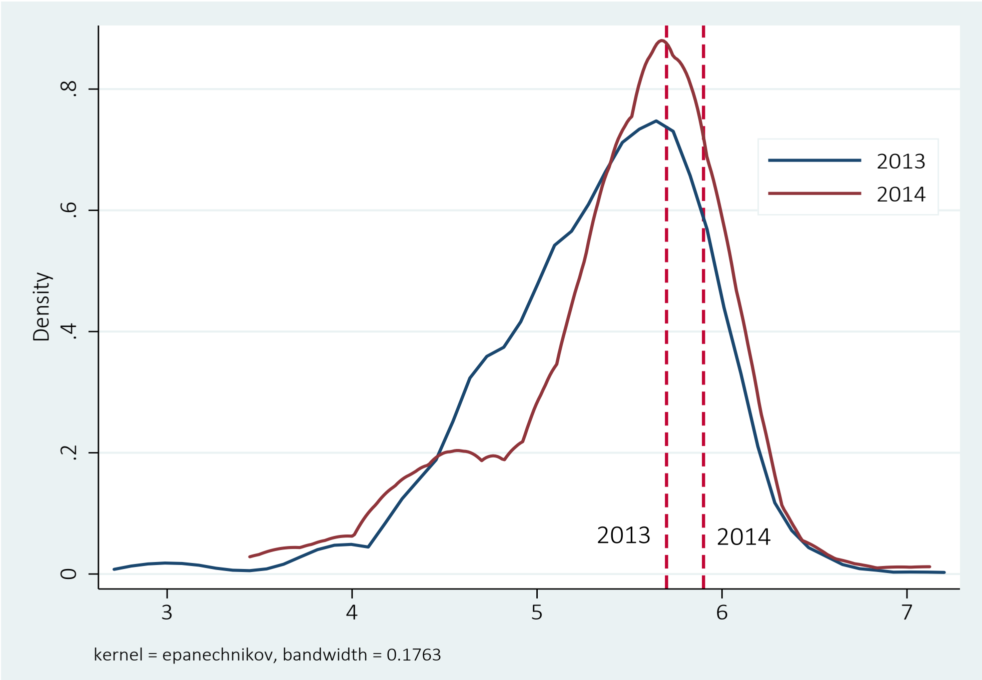

Figure 4: Kernel Density Estimates of the Log of Real Monthly Wages, 15-Year-Old Males (2013-2014). *Source:* Own calculations using 2013-2014 HLFS. *Notes:* Workers do not attend school while working. Appropriate weights are used. Dashed lines refer to the log of average minimum wage in a year in real terms.

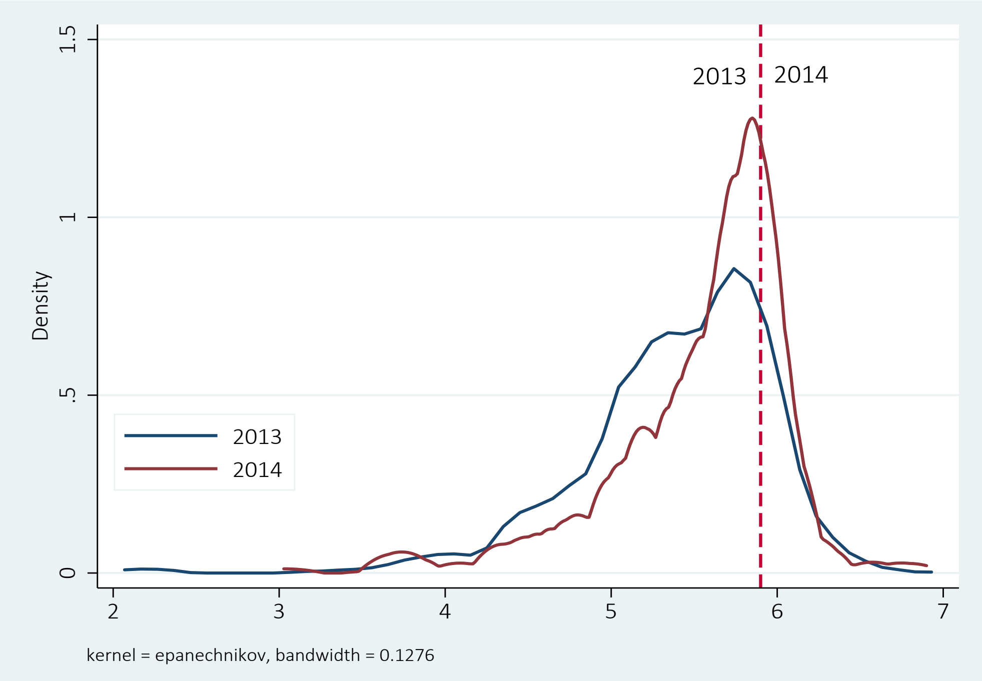

Figure 5: Kernel Density Estimates of the Log of Real Monthly Wages, 16-Year-Old Males (2013-2014). *Source:* Own calculations using 2013-2014 HLFS. *Notes:* Workers do not attend school while working. Appropriate weights are used. Dashed lines refer to the log of average minimum wage in a year in real terms.

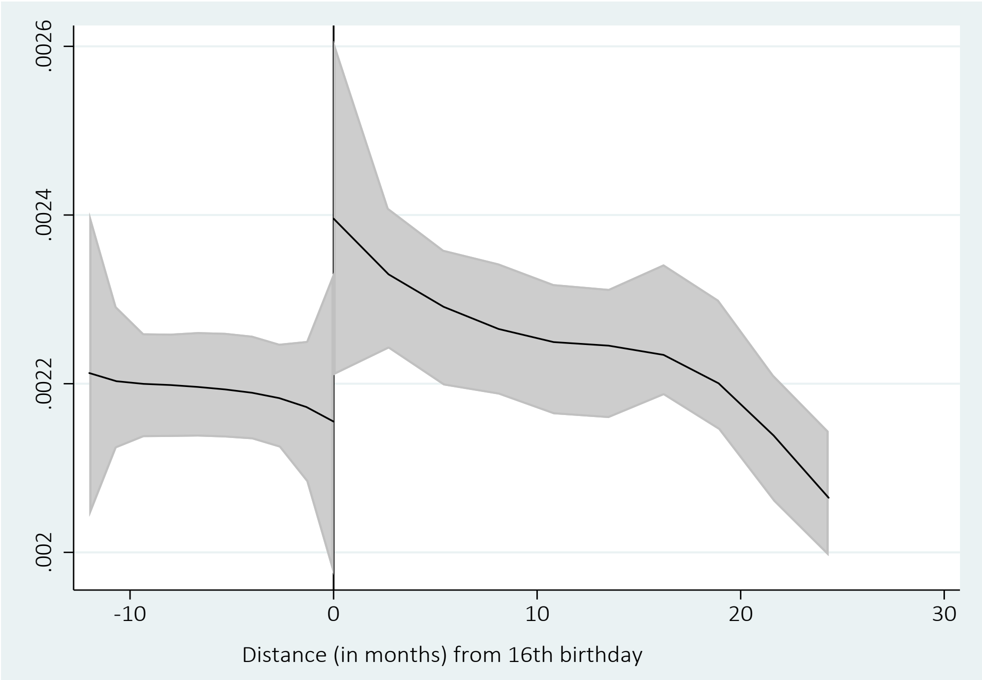

Figure 6: Manipulation test using local polynomial density estimation. *Source:* Own calculations using SILC data.

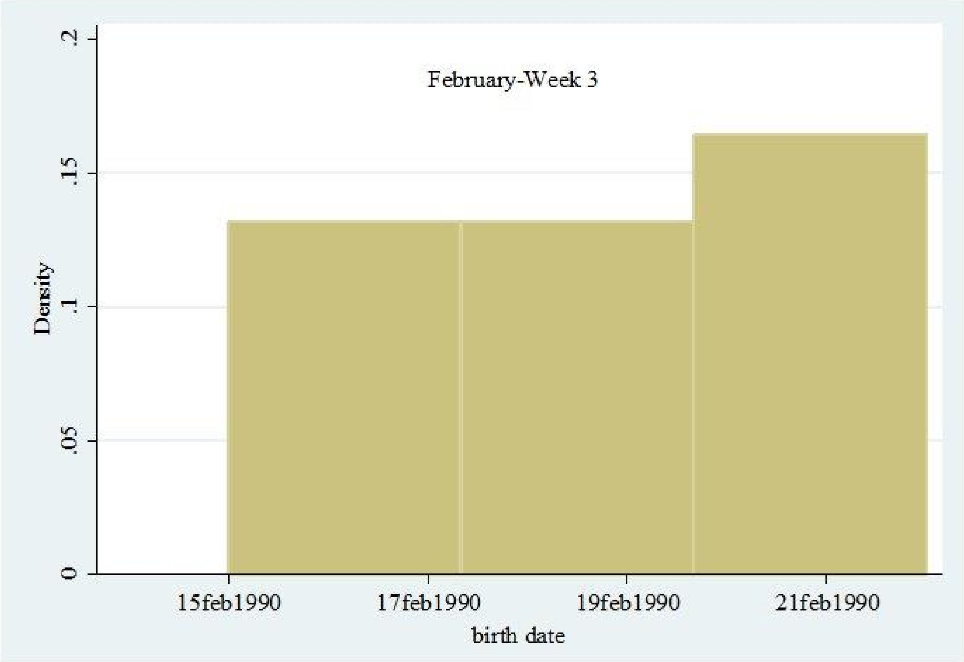

Figure 7: Histogram of Males Born on Each Day of the Third Week of February 1990.
Source: Own calculations using Turkish Employment Agency data.

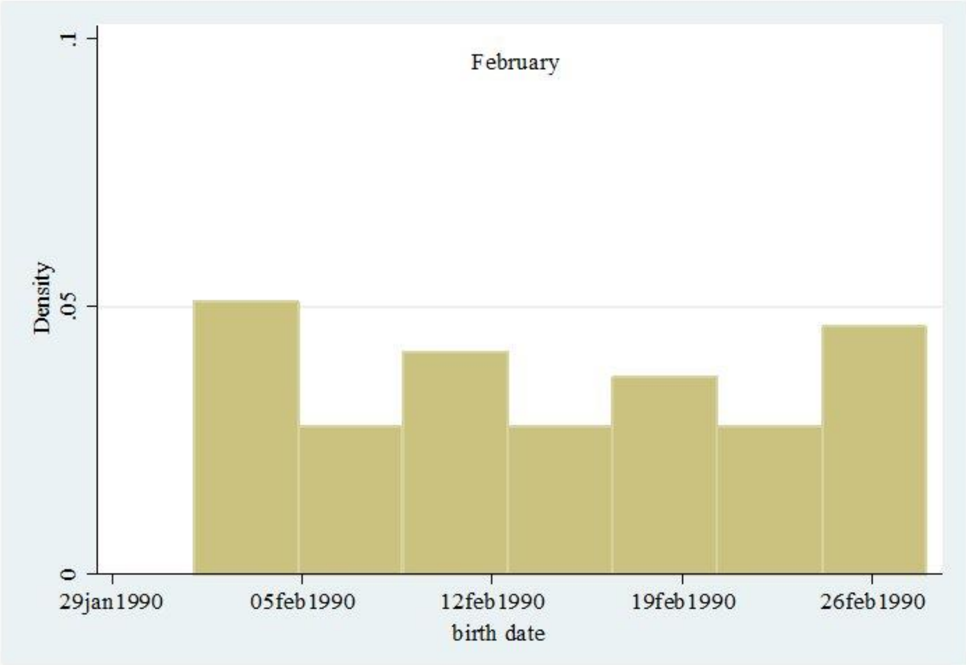

Figure 8: Histogram of Males Born in the Month of February 1990. *Source:* Own calculations using Turkish Employment Agency data.

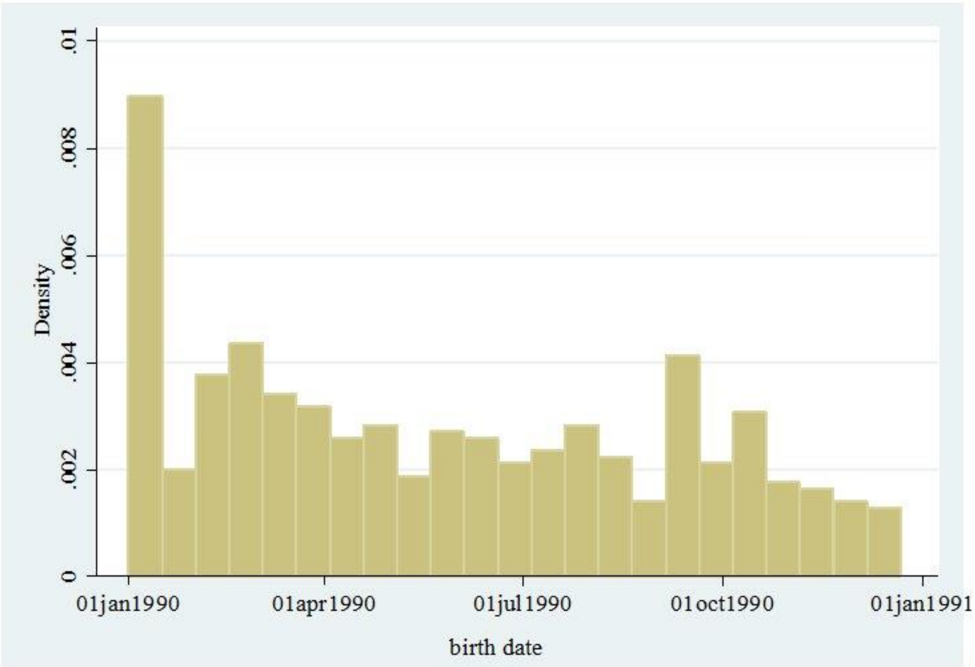

Figure 9: Histogram of Males Born in 1990. *Source:* Own calculations using Turkish Employment Agency data.

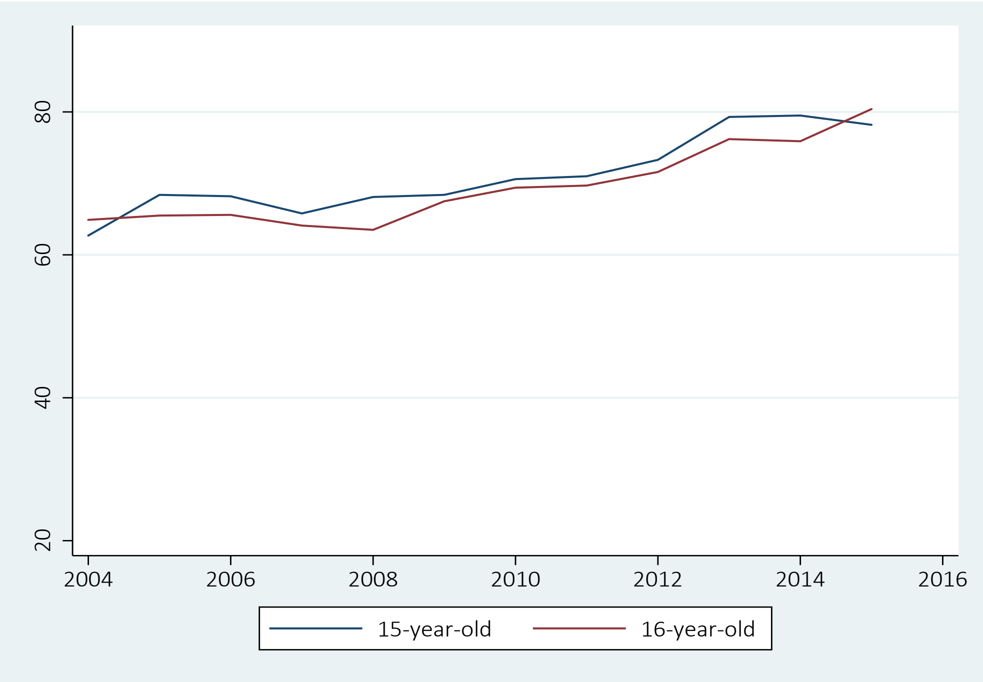

Figure 10: High School Enrollment Rates of Males (2004-2015). *Source:* Own calculations using 2004-2015 HLFS.

Summary statistics (2013, males)

	Age 16	Age 15
Years of educ.	7.6	7.6
Years of job tenure	1.4	1.1
Household size	4.1	4.2
Log real monthly wage	5.4	5.3
Salaried worker	0.12	0.07
Employed	0.17	0.12
In education	0.70	0.78
Neither in emp. nor in ed.	0.13	0.10
Unemployed	0.10	0.07
In labor force	0.27	0.19
In good health	0.92	0.91
Hours of work	50.43	43.80
# of observations	7,012	7,244

Table 1: **Summary statistics for males (2013).** *Source:* Own calculations using the SILC data set.

Summary statistics (2014, males)

	Age 16	Age 15
Years of educ.	7.6	7.6
Years of job tenure	1.3	1.0
Household size	4.1	4.2
Log real monthly wage	5.6	5.3
Salaried worker	0.12	0.06
Employed	0.18	0.09
In education	0.71	0.81
Neither in emp. nor in ed.	0.10	0.10
Unemployed	0.09	0.08
In labor force	0.27	0.17
In good health	0.92	0.93
Hours of work	48.45	49.58
# of observations	7,260	7,303

Table 2: **Summary statistics for males (2014).** *Source:* Own calculations using the SILC data set.

Estimation Results for RDD model (males)

	Salaried worker	Employed	Unemployed	In labor force	In education	Neither in em. nor ed.
Panel A: Local Linear Regression						
Estimated coefficient(1)	-0.019***	-0.031***	0.019***	-0.013	0.014*	0.018***
	(0.007)	(0.01)	(0.003)	(0.01)	(0.008)	(0.004)
h	12.82	12.67	19.19	13.01	12.45	19.98
Effective # of Observations	7,179 (left)	7,179 (left)	7,244 (left)	7,179 (left)	7,179 (left)	7,179 (left)
	7,432 (right)	7,432 (right)	11,574 (right)	7,972 (right)	7,432 (right)	11,261 (right)
Estimated coefficient(2)	-0.015*	-0.025**	0.019***	-0.01	0.01	0.018***
	(0.008)	(0.011)	(0.003)	(0.011)	(0.009)	(0.004)
h	9.08	8.98	13.59	9.21	8.82	14.15
Effective # of Observations	5,374 (left)	4,780 (left)	7,244 (left)	5,374 (left)	4,780 (left)	7,179 (left)
	5,766 (right)	5,201 (right)	8,123 (right)	5,766 (right)	5,201 (right)	8,523 (right)
Panel B: Logistic Regression						
Estimated coefficient	-0.016***	-0.026***	0.022***	-0.01	0.013	0.018***
	(0.007)	(0.007)	(0.003)	(0.010)	(0.008)	(0.004)
h	6	6	6	6	6	6
# of Observations	7,670	7,670	7,749	7,670	7,670	7,670
Estimated coefficient	-0.036***	-0.045***	0.022***	-0.026***	0.022***	0.025***
	(0.009)	(0.009)	(0.002)	(0.008)	(0.007)	(0.004)
h	12	12	12	12	12	12
# of Observations	14,070	14,070	14,256	14,070	14,070	14,070
Panel C: OLS Regression						
Estimated coefficient	-0.021**	-0.030**	0.021***	-0.009	0.012	0.018***
	(0.008)	(0.011)	(0.002)	(0.01)	(0.008)	(0.004)
h	6	6	6	6	6	6
# of Observations	7,670	7,670	7,749	7,670	7,670	7,670
Estimated coefficient	-0.031***	-0.043***	0.020***	-0.023**	0.020**	0.023***
	(0.006)	(0.009)	(0.002)	(0.009)	(0.008)	(0.003)
h	12	12	12	12	12	12
# of Observations	14,070	14,070	14,256	14,070	14,070	14,070

Table 3: Source: Own calculations using SILC. *Notes:* ***, ** and * refer to 1%, 5% and 10% significance levels, respectively. Estimated coefficients in logit estimates correspond to discrete change in the probability. Quarterly calendar time dummies (Last quarter is the reference) and month of birth dummies (December is the reference) are used. *1* MSE Optimal Bandwidth. *2* CER Optimal Bandwidth.

Estimation Results for Diff-in-Disc model (males)

	Salaried worker	Employed	Unemployed	In labor force	In education	Neither in em. nor ed.
Panel A: Logistic Regression						
Estimated coefficient	-0.034***	-0.057***	0.032***	-0.031***	0.027***	0.036***
	(0.004)	(0.005)	(0.007)	(0.008)	(0.007)	(0.006)
h	6	6	6	6	6	6
# of Observations	15,348	15,348	15,348	15,348	15,348	15,348
Estimated coefficient	-0.013**	-0.036***	0.021***	-0.016**	0.017**	0.020***
	(0.006)	(0.006)	(0.005)	(0.007)	(0.008)	(0.006)
h	12	12	12	12	12	12
# of Observations	28,186	28,186	28,186	28,186	28,186	28,186
Panel B: OLS Regression						
Estimated coefficient	-0.034**	-0.059**	0.028***	-0.032***	0.025***	0.034***
	(0.005)	(0.006)	(0.006)	(0.008)	(0.008)	(0.006)
h	6	6	6	6	6	6
# of Observations	15,348	15,348	15,348	15,348	15,348	15,348
Estimated coefficient	-0.012	-0.032***	0.019***	-0.014	0.01	0.021***
	(0.007)	(0.008)	(0.005)	(0.008)	(0.008)	(0.006)
h	12	12	12	12	12	12
# of Observations	28,186	28,186	28,186	28,186	28,186	28,186

Table 4: **Source:* Own calculations using SILC. *Notes:* ***, ** and * refer to 1%, 5% and 10% significance levels, respectively. Estimated coefficients in logit estimates correspond to discrete change in the probability. Quarterly calendar time dummies (Last quarter is the reference) and month of birth dummies (December is the reference) are used.

Estimation Results for RDD model (males, 2015-2016)

	Salaried worker	Employed	Unemployed	In labor force	In education	Neither in em. nor ed.
Estimated coefficient*	0.0004	0.001	-0.002	-0.001	0.004	-0.005
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)
h	14.52	17.33	14.53	15.82	15.97	14.71
Effective # of Observations	12,913 (left)	12,913 (left)	12,913 (left)	12,913 (left)	12,913 (left)	12,913 (left)
	16,219 (right)	19,198 (right)	16,219 (right)	17,228 (right)	17,228 (right)	16,219 (right)
Estimated coefficient**	0.0007	0.0003	-0.002	-0.003	0.006	-0.005
	(0.003)	(0.009)	(0.003)	(0.004)	(0.004)	(0.003)
h	10.25	12.24	10.26	11.17	11.28	10.39
Effective # of Observations	10,776 (left)	12,913 (left)	10,776 (left)	11,842 (left)	11,842 (left)	10,776 (left)
	12,024 (right)	14,146 (right)	12,024 (right)	13,100 (right)	13,100 (right)	12,024 (right)

Table 5: Source: Own calculations using SILC. *Notes:* ***, ** and * refer to 1%, 5% and 10% significance levels, respectively. Quarterly calendar time dummies (Last quarter is the reference), month of birth dummies (December is the reference) and a year dummy for 2016 are used. *1* MSE Optimal Bandwidth. *2* CER Optimal Bandwidth.

Estimation Results for RDD model with Moulton correction (males)

	Salaried worker	Employed	Unemployed	In labor force	In education	Neither in em. nor ed.
Estimated coefficient*	-0.021**	-0.030***	0.021***	-0.009	0.012	0.018***
	(0.007)	(0.01)	(0.003)	(0.01)	(0.009)	(0.004)
h	6	6	6	6	6	6
# of Observations	7,670	7,670	7,749	7,670	7,670	7,670
Estimated coefficient**	-0.031***	-0.043***	0.020***	-0.023***	0.020***	0.023
	(0.006)	(0.007)	(0.003)	(0.007)	(0.007)	(0.003)
h	12	12	12	12	12	12
# of Observations	14,070	14,070	14,256	14,070	14,070	14,070

Table 6: Source: Own calculations using SILC. *Notes:* ***, ** and * refer to 1%, 5% and 10% significance levels, respectively. Clustered standard errors are adjusted for Moulton correction. Quarterly calendar time dummies (Last quarter is the reference) and month of birth dummies (December is the reference) are used.