2015

Essays in Labor Economics

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ESSAYS IN LABOR ECONOMICS

A Dissertation

Submitted to the Graduate Faculty of the
Louisiana State University and
Agricultural and Mechanical College
in partial fulfillment of the
requirements for the degree of
Doctor in Philosophy

in

The Department of Economics

by
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August 2015

This dissertation is dedicated to my parents Yusuf and Halise Filiz…

ACKNOWLEDGEMENTS

I have been very fortunate to work with my advisor and dissertation committee chair Dr. Naci Mocan throughout my studies at Louisiana State University. I would like to express my deepest gratitude to him for being a great mentor and always having time to discuss research. His support, guidance and encouragement have been a constant inspiration for me.

I would like to thank my dissertation committee members, Dr. Robert Newman and Dr. Ozkan Eren for their advice and support on my research. I have immensely benefited from my discussions with them. I would also like to thank the Dean’s Representative, Dr. Kevin McCarter, for serving on my committee. In addition, I would like to extend my thanks Mary Jo Neathery and Judy Collins for taking care of all administrative work during my studies.

Many people have touched my life on academic and/or personal level along this journey. I would like to thank them all, but especially to my dear friends and colleagues Bahadir and Elif Dursun, Duha Altindag, Zuhal and Emre Unlu, Luiza Pogorelova, Justin Cook, Chandan Jha and Colin Cannonier for their encouragement, support and sincere friendship through hard and good times. I also am grateful to my best friends Erman Yenigun and Gozde Altunbek for their love, unconditional support and encouragement I had over the years.

Finally, I would like to thank my parents, Yusuf and Halise Filiz, my brother Dincer Filiz, my sister-in-law Tsveta Karadjova Filiz, my nephew Dalyan Filiz, and my grandparents Ayse and Yusuf Mutlu for their endless love, encouragement and support. Without them, I wouldn’t be able to pursue my dreams and goals. I am where I am today, thanks to you!

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ABSTRACT

In this dissertation, I present three distinct topics on labor economics that can be read independently from one another. In the first chapter, using matched mother-child data from the National Longitudinal Survey of Youth, I investigate the impact of mothers' involuntary job loss on children's academic achievement. In the next chapter, I examine the impact of eye and hair color on wages-at-first-job after schooling. In addition, I investigate whether hair color has an impact on the wage-at-the-first-job if the individual resides among people who have similar features. In the last chapter, I examine the impact of unemployment insurance benefit generosity on benefit duration and labor market transitions in Turkey with a regression discontinuity design.

CHAPTER 1. INTRODUCTION

This dissertation consists of three distinct essays within the broad field of labor economics. In Chapter 2, I investigate the impact of mother's involuntary job loss on her children's academic achievement. In the next chapter, I examine the impact of hair and eye color on the first-job-after schooling. In Chapter 4, I study the impact of unemployment insurance generosity on unemployment duration, labor market transitions, cheating the system and rejecting services of the Employment Agency.

1.1. MOTHERS' INVOLUNTARY JOB LOSS AND CHILDREN'S ACADEMIC ACHIEVEMENT

This chapter investigates the impact of mother's involuntary job loss on her children's academic achievement. I utilize a matched mother-child data from the National Longitudinal Survey of Youth 1979. I define job displacement as an involuntary job loss due to plant closure. I find that mother's job displacement has a negative impact on her children's academic achievement, which is measured by PIAT math and reading test scores. In addition, the impact of the mother's job displacement on her child's test scores is different for single mother and married mother families. I find that there is a negative impact of mother's job displacement on child's both test scores for single mothers only. However, there is no evidence that job displacement affects test scores of the children of married mothers.

I investigate two possible channels through which mother's job displacement affects test scores: income and child behavioral problems. The results show that mother's job displacement has a negative impact on her and the family's income. In addition, her job displacement increases behavioral problems of the child. I find evidence that mother income and child's behavioral problems are channels through which mother's job displacement affects math and reading test scores.

1.2. IT PAYS OFF TO BE BLOND IN A NON-BLOND NEIGHBORHOOD: EYE COLOR, HAIR COLOR, ETHNIC COMPOSITION AND STARTING WAGES

In Chapter 3, I investigate the impact of physical appearance, eye and hair color, on the wage at-the-first-job-after completing schooling. In addition, I investigate whether the impact of hair color persists if the individual resides among people who have the similar features. I utilize two data sets: National Longitudinal Survey of Youth 1979 and Census of Population 1980. The results show that having blonde hair has a positive impact on the wage-at-the-first-job particularly for females and whites. There is no evidence suggesting eye color has an effect on starting wages.

In order to investigate whether the impact of hair color is still observed in a county where the majority of people have the similar features, I link ethnic origin/ancestry information collected by census to three anthropological studies classifying ethnic groups by their hair and eye color. If the share of light featured ethnic groups (ethnic groups that are identified by blonde, red hair and blue/green/hazel eyes) is greater than fifty-percent, the county is considered as "light-featured," whilst it is considered as "dark-featured" if the share is less than fifty-percent. I find that blonde females residing in counties where brown/black hair is the common feature earn more compared to females with brown/black hair and residing in the same county. There is some evidence that individuals with brown/black hair and residing in a light-featured county get a wage penalty compared to their counterparts residing in a dark-featured county.

1.3. THE EFFECT OF UNEMPLOYMENT INSURANCE GENEROSITY ON UNEMPLOYMENT DURATION AND LABOR MARKET TRANSITIONS: EVIDENCE FROM TURKEY

In Chapter 4, I investigate the impact of unemployment insurance generosity on unemployment duration, labor market transitions, cheating the system and rejecting services of the Employment Agency. Turkey has enacted the Unemployment Insurance Law around two decades ago. According the law, workers who pay premium for at least 600 days are eligible to receive unemployment insurance benefits (along with other criteria). If the worker has less than 900-paid-premium-days, she is eligible to 6-month UI benefits. However, if she has 900 or more paid-premium-days, she is entitled to 8-month UI benefits. The two-month difference is considered as "benefit extension/generosity." I utilize regression discontinuity design and use local linear regressions to investigate the relationship between benefit generosity and outcomes. The identification comes from the discontinuity of outcome variables at the cutoff, which is 900-paid-premium-days.

I find that the unemployment insurance generosity increases unemployment duration by 0.7 weeks and decrease the probability of entering employment by six-percentage points in Turkey. These finding are greater than the findings of studies investigating the impact of benefit generosity on unemployment duration and probability of finding a job for developed countries. Many of the studies do not investigate transition to non-participation in the labor force. I find that benefit generosity has no impact on the probability of entering non-participation, however, there is evidence that it leads to a decrease in non-participation in the labor force for single benefit takers. Moreover, unemployment insurance generosity decreases the probability of cheating the UI system and rejecting the Turkish Employment Agency's services.

Chapter 5 summarizes the findings of these three studies.

CHAPTER 2. MOTHERS' INVOLUNTARY JOB LOSS AND CHILDREN'S ACADEMIC ACHIEVEMENT

2.1. INTRODUCTION

In families where women are income earners, the job loss of women is expected to affect the well-being of the family. Between 2007 and 2009, 6.9 million workers were displaced from their jobs in the U.S. and two-fifths of these displaced workers were women (Bureau of Labor Statistics, 2011).[1] In this study, I use the National Longitudinal Survey of Youth 1979 (NLSY79) and National Longitudinal Survey of Youth 1979 Child/Young Adult Survey (NLSY79-CS) to investigate the effect of mothers' job displacement on children's academic achievement during the period 1988-2002. Job displacement is defined as an involuntary job loss due to plant closure. The educational achievement of the child is measured by math and reading scores from the Peabody Individual Achievement Tests (PIATs).

The negative impact of job displacement on income, consumption, health, and family structure has been well documented in the literature. For example, Kletzer and Fairlie (2003), Jocobson, LaLonde and Sullivan (1993), Stevens (1995), and Ruhm (1991a, 1991b) show that following job displacement, the earnings of workers decline by 10 to 25 percent. Furthermore, Browning and Crossley (2006) find that layoffs reduce family consumption by 4 to 10 percent. Ruhm (1991a, 1991b) concludes that displaced workers experience longer unemployment spells.

Involuntary job loss not only affects income, but also affects family dynamics and health of the individual. Sullivan and von Wachter (2009) find that the mortality rate of employees who were displaced is higher compared to the workers who were not displaced. Although their study covers a small sample of workers from Pennsylvania, this result is significant in terms of the

[1] http://www.bls.gov/cps/wlf-databook-2011.pdf

impact of job displacement on parents' health. Using two data sets, Americans' Changing Lives Study and Wisconsin Longitudinal Study, Burgard, Brand and House (2007) find that involuntary job loss causes poorer physical health and it increases depressive symptoms. Following a job loss, the individual may experience marriage problems, often leading to separation or divorce (Charles and Stephens, 2004).

These negative effects of involuntary job loss may spread to children. The potential channels through which these effects reach and affect children can be classified under two main mechanisms: income and depression/stress. The decrease in family income due to displacement limits the financial resources available for children. Particular channels through which this effect works includes less spending on education, health, food, and social activities. Shea (2000), using the Panel Study of Income Dynamics and job loss as an exogenous shock to income, finds that parental income has a negligible effect on child's future labor market earnings and years of schooling. However, Oreopoulos, Page and Stevens (2008) find that individuals whose father experienced job loss when they were children have lower annual earnings compared to children whose father did not experience job loss. Coelli (2011) investigates the impact of job loss on child's educational outcomes by using the Canadian Survey of Labour and Income Dynamics and concludes that parental job loss decreases the probability of attending university and increases the probability of dropping out of high school. Dahl and Lochner (2012) investigate the effect of family income on child's test scores by using the NLSY79, and find that a $1,000 increase in family income leads to 2.1 and 3.6 percent of a standard deviation increase in math and reading test scores, respectively.

There are several potential reasons for a psychological disturbance following a job loss. For example, McLoyd (1989) defines the economic loss caused by job loss as a stressor and “crisis-provoking event” for which parents were not prepared. In addition, parents may be stressed because being jobless may be associated with loss of social status and shame, or because they may be stressed during the process of looking for a new job. As a result, a parent’s attitude towards children may change. For example, parents may pay less attention to a child’s needs, or they may be abusive. The new emotional and psychological environment at home may disturb the child. A child’s concentration at school and motivation for school and education related activities may decrease and the child’s expectations about the future may be impacted. On the other hand, there may be a positive effect of the mother being at home. Following a job separation, the mother may have additional time to spend with her children. The mother may be able to supervise children better, help with schoolwork, cook healthy foods at home, and increase interaction with her children. If the increase in time spent together is also quality time, then there may be a positive impact of job displacement on child development. Since the mother is usually the primary care giver of children in most cases, the extra time may increase child’s educational outcome.

Studies focusing on the impact of parental job displacement on child’s educational outcome generally find a negative effect. For example, Stevens and Schaller (2011) use Survey of Income and Program Participation and conclude that the job loss of parents increases the probability of grade repetition by 15-percent. Kalil and Ziol-Guest (2008) investigate the relationship between parental employment experiences and their children’s grade repetition and school suspension/expulsion. They find that the probability of grade repetition is two times higher and the probability of expulsion/suspension is two and a half times higher for children whose fathers experienced involuntary job loss, compared to children whose fathers did not lose their job. Rege, Telle and Votruba (2011), using data from Norway, find that parental job loss has a negative effect on child's school performance, which is measured by grade point averages (GPA) of graduating secondary school students.

The current chapter provides three contributions to the existing literature. First, there are not many studies focusing on the impact of mother's job loss on child outcomes. Rege et al. (2011), and Kalil and Ziol-Guest (2008) are the only studies, to the best of my knowledge, which investigate the impact of mother's job loss separately from the father's job loss. Kalil and Ziol-Guest (2008) find that the employment patterns of the mother do not affect academic progress. However, for a family in which both the mother and father work, economic welfare and family well-being may well be altered by not only the father's but also by the mother's job loss. Moreover, they focus on job separations that take place due to slack business and work conditions, being unable to find a job, labor dispute, illness or disability, and other reasons. The exogeneity of these reasons is open to debate. Rege et al. (2011) find a positive but statistically insignificant effect of mother's displacement on the child's 10th grade GPA. Thus, the question whether mother's job displacement plays a role in academic achievement of children requires further investigation.

Second, this study utilizes the exact timing of the displacement incidence of the mother and educational outcome of the child. NLSY provides a detailed work history of mothers[2], which enables me to observe the date of the displacement. The administration date of the PIAT tests is the child's interview date. Thus, I can measure three intervals with precision: first, the time interval between tests taken by children, second, the time interval between the displacement event and the test dates and third, the duration of unemployment following job displacement. In a particular survey year the child takes the test at the interview date. In order to observe the link

[2] The data does not provide information on father's work history.

between mother's job displacement and the child's test score, I can distinguish whether the test was taken before or after the displacement incidence. Thus, using the detailed event dates in NLSY, I can accurately link the date of displacement to the date of the test.[3]

Third, in this study I employ a mother-child matched data set provided by the NLSY79 and NLSY79-CS.[4] The matched data set provides detailed demographic characteristics of the mother and the child, work history of the mother, and the child's achievement test scores. Starting 1986, children who are five years and older are administered PIATs. There are three PIAT assessments: math, reading recognition and reading comprehension. In this study, I will focus on PIAT in mathematics (PIAT-Math) and in reading recognition (PIAT-Reading). Since the NLSY79-CS is a biennial survey, for children ages 5 to 14, it is possible to observe the achievement score of the same child for up to 5 periods.[5]

[3] Stevens and Schaller (2011) utilize the job loss that occurred in the year of grade repetition and one or more years prior to the grade repetition to investigate the impact of parental job loss. However, it might be the case that a parent lost her/his job at either the very beginning or end of the school year. The impact of the former is expected to be different than the latter. If the length of time between displacement and the test is not controlled for, the same weight will be attributed to the displacement that occurred in a closer date to test date and to the displacement that occurred in a distant time. Similarly, in Kalil and Ziol-Guest (2008), the timing of the displacement is set to be within a twenty-four month window, but the actual length of the time between involuntary job loss and education outcome is not considered. Another study investigating the link between parental unemployment and test scores is Levine (2011). He finds that father's or mother's unemployment does have much effect on children's test scores. However, he does not separate unemployment by reasons.

[4] To the best of my knowledge, the only study using the same data set to investigate the association between job displacement and child outcomes is Wightman (2009). Although the NLSY79 does not provide detailed work history for the fathers (spouses), he focuses on either parent's job loss by considering fathers (spouses) who were not working in the previous year as displaced due to "any reason" This set up of involuntary job loss is problematic because job loss due to illness, being fired, seasonal jobs, etc. are not exogenous shocks.

[5] If a child takes the test when s/he is 5 years old for the first time, s/he can take the test again at the ages 7, 9, 11 and 13. When s/he is 15, s/he is not administered the test. Note that the child might not necessarily take the test in consecutive survey years.

Using a matched mother-child sample from NLSY79, I find evidence that mother's job displacement affects child's reading and math scores negatively. The results are different for single and married mother samples. I find that job displacement of a *single* mother generates lower reading and math scores. This impact is due to displacement that occurred one year prior to the test date and lasted up to twelve months. I cannot find evidence that a married mother's job displacement affects test scores. Controlling for child fixed-effects reduces the estimated impacts but statistical significance is retained for reading score. In addition, the falsification test supports the assumption that mother's job displacement due to plant closure is exogenous. Finally, the results from the strategy introduced by Oster (2015) suggest that the results are causal.

The rest of the chapter proceeds as follows: Section 2 describes the empirical specification, Section 3 introduces the data and descriptive statistics, Section 4 presents the results and Section 5 concludes.

2.2. EMPIRICAL SPECIFICATION

Equation [1] depicts a child's academic success (school performance) as a function of her/his own attributes and the family characteristics.

$$A = f_1(\boldsymbol{X}, \boldsymbol{PI}, \boldsymbol{Z}) \qquad \textbf{[1]}$$

where A is the academic achievement of the child, $\boldsymbol{X}$ is a vector of child characteristics and $\boldsymbol{PI}$ is the parental investment which is a function of characteristics of parents, children, and family income. $\mathbf{Z}$ stands for the mother characteristics. Equation [2] represents parental investment as a function of family income, Y, the quality and quantity of time spent with children, QT, the characteristics of the child and the mother, X and Z respectively, and a family shock, D.

$$PI = f_2(\boldsymbol{X}, Y, QT, \boldsymbol{Z}, D) \qquad \textbf{[2]}$$

D stands for the involuntary job loss of the mother. Job displacement might affect parental investment directly as depicted in Equation [2], but also indirectly through channels such as reduction in income, change in the quality and quantity of time spent with children and other unobserved channels. For example, uncertainty about the future, change in the family structure (e.g. divorce and separation) and the child's perception about education following a job displacement might decrease the investment in children.

Family income consists of mother income (MI) and non-mother income (NMI). Mother's income includes components such as income from her wages, salary, and tips, military income, income from farm and business and unemployment compensation. The other family income includes spouse or partner's income from wages and salary, his income from military, income from farm and business, unemployment compensation, income of other family members, welfare payments, child support and alimony, and income from sources other than family members. Thus, family income is $\mathrm{Y} = \mathrm{MI} + \mathrm{NMI}$, where $MI = f(D, \boldsymbol{Z})$. Mother's job displacement is expected to reduce mother's income. These arguments indicate that family income, Y, can be represented as:

$$\mathrm{Y} = f_3\ (\mathrm{NMI}, \mathrm{D}, \mathbf{Z}) \qquad \textbf{[3]}$$

The quality and the quantity of time the mother spends with children, QT, is a function of family income, displacement, and mother characteristics. Since family income consists of both mother and non-mother income I can write quality and quantity of time as:

$$QT = f_4(D, NMI, \boldsymbol{Z}) \quad \textbf{[4]}$$

Substituting equations 3 and 4 into equation 2, and equation 2 into equation 1 yields a reduced form where $A = f_1(\boldsymbol{X}, NMI, D, \boldsymbol{Z})$. The estimation equation therefore is:

$$A_{ijt} = \alpha + D_{ijt}\Omega' + \boldsymbol{X_{ijt}\beta'} + NMI_{\boldsymbol{ijt}}\boldsymbol{\delta'} + \boldsymbol{Z_{ijt}\psi'} + \lambda_t + \boldsymbol{e_{ijt}} \quad \textbf{[5]}$$

where A_{ijt} stands for academic achievement of child *i* of mother *j* at time *t*, where *t* is the child's test date.[6] D_{ijt} represents the mother's job displacement. $\boldsymbol{X_{ijt}}$ is a vector of child characteristics which includes gender, race, birth order, age indicators, number of siblings, and the type of school the child attends. $\boldsymbol{Z_{ijt}}$ is a vector of mother characteristics. This vector includes education status of the mother, mother's age at birth of child *i*, whether the household resides in an urban area, and marital status of mother. There is no information on the father's work history in the NLSY79. Thus, I cannot control for father's work status.

Estimation of equation [5] will provide an unbiased estimate of the displacement coefficient under the assumption that involuntary job loss is independent of mother and child characteristics. This may be a strong assumption. In the literature, both layoffs and plant closures are utilized as exogenous reasons of job loss (for example Kletzer and Fairlie, 2003; Ruhm,

[6] If the child's interview date is missing, the mother's interview date is employed as child's interview date.

1991a and 1991b; Charles and Stephens, 2004; etc). Involuntary job loss due to being laid off, however, might be correlated with the characteristics of the mother. For instance, a mother with relatively low productivity is more likely to be laid off instead of a mother with relatively high productivity. If the mother's productivity is not related to the child's test score, then layoffs can be used in the analysis. However, if mothers who are more productive at work are also more productive at home regarding home production, the productivity differences will have an impact on the test scores. Thus, I focus on displacements related to plant closures as indicators of involuntary job loss.[7] Equation [5] includes year dummies in order to control for unobserved year effects, λ_t.

2.3. DATA

To analyze the impact of mother's job displacement on child's educational outcome a child-mother matched data set is required. The National Longitudinal Survey of Youth 1979 (NLSY79), and the National Longitudinal Survey of Youth 1979 Child/Young Adult Survey (NLSY79-CS) provide such a matching for mothers and their children. NLSY79 includes 12,686 individuals, 6,403 males and 6,283 females, who were initially interviewed in 1979 and were aged 14-21 as of December 1978. The NLSY79 was conducted annually from 1979 to 1994, and biennially thereafter. The NLSY79-CS includes the children who were born to female respondents of NLSY79. NLSY79-CS survey started at 1986 and has been conducted biennially thereafter.

[7] Some studies include being fired or discharged as a reason of an involuntary job loss. For example Steven and Schaller (2011) and Wightman (2009) employ being fired a reason of involuntary job loss. Following Kletzer and Fairlie (2003) I exclude being fired/discharged from the analyses due to the same concerns I exclude layoffs.

The NLSY79 provides information on earnings, marriage, demographic and many other characteristics of the mother. The NLSY79-CS provides information on child characteristics as well as several assessment measures such as academic achievement, temperament, motor and social development, and behavioral problems.

2.3.1. Test Scores: Peabody Individual Achievement Tests

Beginning in 1986, children who were aged five and above were administered the Peabody Individual Achievement Tests (PIAT) in mathematics (PIAT-Math), in reading recognition (PIAT-Reading), and in reading comprehension (PIAT-Comp).[8] Children receive a PIAT-Comp only if they get a certain score on PIAT-Reading. Thus, I focus only on the PIAT-Math and PIAT-Reading. The NLSY79 guides define PIAT-Math as a measure of child's mathematical attainment as it is taught in mainstream education.[9] It includes 84 questions that can be solved mentally. According to PIAT manual the mathematics test is designed to measure the ability of applying mathematical knowledge to solve practical problems (Dunn and Markwardt, 1970). Thus, it is not only measuring the knowledge of mathematics, but also the ability to use this knowledge. PIAT-Reading is defined as an oral reading test and measures word recognition and pronunciation ability, which are essential components of reading achievement.[10] It is also noted that reading ability is a sign of a "cultured person," which might be accepted as an asset in the process of human capital accumulation. These measures are accepted as highly reliable and valid assessments of a child's academic achievement and are utilized by many researchers as a measure of achievement (Todd and Wolpin, 2007; Dahl and Lochner, 2012).

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[8] After 1994, the test is given to children aged 5-14 only. Thus, the sample consists of children of this age range.
[9] http://www.nlsinfo.org/childya/nlsdocs/guide/assessments/PIATMath.htm
[10] http://www.nlsinfo.org/childya/nlsdocs/guide/assessments/PIATReading.htm

In this study, the standardized PIAT scores are utilized. PIAT scores have a mean of 100 and standard deviation of 15. Since the NLSY79-CS is a biennial survey, for children aged 5-14 it is possible to observe the achievement score of the same child for up to 5 periods.

2.3.2. Mother's Job Displacement

One of the advantages of the NLSY79 is to have access to detailed work history of respondents. In each survey year, the respondents provide the start-end dates, and the reason for leaving each job for up to five jobs.[11] Thus, from the work history it is possible to identify the exact date of a job loss.[12] I define mother's job displacement as job loss due to plant closure. The job displacement is measured by D_{ijt}, and t represents the date the PIAT was administered. D_{ijt} takes the value of one if the child's mother is displaced any time within the 24-month period prior to the child's test date. For each child, I create a 24-month window that has the test day as the starting point. For example, if the child takes the test on 12th of March, 2000, the window in which the mother might experience job displacement begins at 3/12/1998 and ends at 3/12/2000. If the child's mother *j* is displaced within this period, $D_{ij,2000}$ takes the value of one. Because the children take the test on different dates, I restrict mothers of the control group to those who have three continuous years of work experience. Following the example given above, children in the control group have mothers who have been working continuously for three years (or 36 months) for 2000, 1999 and 1998 survey years. Thus, $D_{ij,2000}$ takes the value of zero for these mothers.

[11] The work history is constructed by following NLSY79 updated Appendix 9, which explains linking the jobs through survey years. After 1998, the mother's work history is known up to 11-12 jobs. However, the reason why respondent left the job is not available for the jobs listed after the fifth. Thus, this information is not utilized in the study.

[12] There is no information on fathers work history. Thus, I cannot control for the father's employment status.

2.3.3. Descriptive Statistics

Table 2.1 reports descriptive statistics for the estimation sample by mother's marital status and the definitions of the variables are given in Appendix A, Table A.1. The PIAT is given to children who are at least 5 years old, and beginning in 1994, the test was no longer given to children older than 14. Thus, the final estimation sample consists of children who are between the ages of 5 and 14. I exclude children who are not living with their mothers since the focus of the study is the interaction between mother and the child. Children who are in the age interval 5-14 but who do not have a test score are excluded from the sample. In addition, since some of the child characteristics are not available for 1986 survey, this survey year is excluded from the analyses. Finally, children whose mothers are not in the labor force and do not satisfy displaced or non-displaced sample criteria are excluded. The final sample consists of 3,111 children between the ages of 5 and 14, living with the mother at the time of interview and have a test score.[13]

The average PIAT-Reading for the all mothers sample is 106. PIAT-Reading is 102 for children whose mother experienced a job displacement, and it is 106 for children whose mother was continuously working during the reference period. The entire sample average of PIAT-Math is 102 and the average for the displaced mothers sample is 99. The average for the PIAT-Math score is lower compared to reading test. Both reading and math test scores are lower for the single mother sample compared to the married mother sample and test scores are higher for non-displaced mothers in both samples. Five-percent of the children in the all mothers sample have mothers who have experienced displacement during the period 1988-2002. For the single mother

[13] There are 1,785 mothers and 199 of them experience an involuntary job loss before the child takes the test. On average, children have two test scores.

Table 2.1
Descriptive Statistics

Variables	All Mothers			Single Mother Sample			Married Mother Sample		
	Entire Sample	Displaced	Non-Displaced	Entire Sample	Displaced	Non-Displaced	Entire Sample	Displaced	Non-Displaced
PIAT Achievement Tests									
PIAT-Reading	106.00	101.90	106.24	102.99	99.42	103.24	107.28	103.67	107.47
	(14.29)	(14.03)	(14.27)	(14.54)	(14.18)	(14.54)	(14.00)	(13.68)	(13.98)
PIAT-Math	102.46	98.97	102.66	99.33	95.55	99.58	103.79	101.42	103.93
	(13.36)	(13.41)	(13.34)	(12.92)	(12.11)	(12.91)	(13.33)	(13.79)	(13.31)
Displacement									
Job Displacement		0.05			0.07			0.04	
		(0.22)			(0.25)			(0.20)	
Unemployment Spell		4.14			4.49			3.87	
		(5.58)			(5.96)			(5.29)	
Child Characteristics									
First Born	0.44	0.42	0.44	0.42	0.45	0.41	0.44	0.39	0.45
	(0.50)	(0.49)	(0.50	(0.49)	(0.50)	(0.49)	(0.50)	(0.49)	(0.50)
White	0.53	0.45	0.53	0.33	0.38	0.33	0.61	0.49	0.61
	(0.50)	(0.50)	(0.50	(0.47)	(0.49)	(0.47)	(0.49)	(0.50)	(0.49)
Female	0.50	0.57	0.50	0.50	0.59	0.50	0.50	0.55	0.50
	(0.50)	(0.50)	(0.50	(0.50)	(0.49)	(0.50)	(0.50)	(0.50)	(0.50)
Number of Siblings	1.47	1.72	1.46	1.44	1.61	1.42	1.48	1.80	1.47
	(0.98)	(1.26)	(0.96	(1.06)	(1.33)	(1.04)	(0.95)	(1.20)	(0.93)
Public School	0.64	0.63	0.64	0.66	0.70	0.66	0.63	0.58	0.63
	(0.48)	(0.48)	(0.48)	(0.47)	(0.46)	(0.48)	(0.48)	(0.49)	(0.48)

(Table 2.1 Continued)

Variables	All Mothers			Single Mother Sample			Married Mother Sample		
	Entire Sample	Displaced	Non-Displaced	Entire Sample	Displaced	Non-Displaced	Entire Sample	Displaced	Non-Displaced
Behavioral Problems [1]									
BPI (Total Score)	103.22	105.24	103.04	105.43	109.34	105.10	102.35	102.56	102.25
	(14.22)	(15.40)	(14.11)	(14.94)	(15.32)	(14.87)	(13.83)	(14.91)	(13.73)
Anti-social	104.18	105.40	104.03	107.07	109.32	106.84	103.03	102.84	102.95
	(13.40)	(14.42)	(13.29)	(14.06)	(14.07)	(13.99)	(12.96)	(14.12)	(12.84)
Anxiety/Depression	101.39	103.60	101.25	102.74	106.70	102.47	100.85	101.58	100.77
	(12.96)	(13.02)	(12.94)	(13.34)	(13.35)	(13.31)	(12.76)	(12.44)	(12.77)
Headstrong	101.23	101.74	101.15	101.74	103.54	101.59	101.03	100.55	100.98
	(12.89)	(13.30)	(12.85)	(13.02)	(13.21)	(12.98)	(12.83)	(13.28)	(12.79)
Hyperactive	102.49	103.60	102.37	103.76	106.68	103.48	101.98	101.58	101.94
	(13.58)	(14.66)	(13.50)	(14.15)	(16.13)	(13.96)	(13.31)	(13.30)	(13.30)
Dependent	104.06	107.20	103.84	106.48	109.39	106.26	103.11	105.76	102.91
	(13.12)	(13.95)	(13.04)	(13.50)	(13.75)	(13.46)	(12.85)	(13.96)	(12.76)
Peer Conflict	103.00	103.84	102.92	103.97	106.52	103.77	102.62	102.08	102.59
	(11.57)	(12.55)	(11.47)	(12.29)	(14.14)	(12.11)	(11.26)	(11.10)	(11.20)
Mother Characteristics									
Family Income [2]	4,895	3,514	4,978	3,061	2,448	3,114	5,673	4,273	5,743
	(2,646)	(1,982)	(2,657)	(1,928)	(1,403)	(1,955)	(2,523)	(1,988)	(2,525)
Mother Income [2]	2,349	1,509	2,400	2,240	1,482	2,301	2,395	1,529	2,441
	(1,358)	(997)	(1,361)	(1,281)	(967)	(1,286)	(1,387)	(1,020)	(1,388)
Non-Mother Income [2]	2,546	2,005	2,578	821	965	813	3,278	2,744	3,303
	(2,077)	(1,623)	(2,095)	(1,253)	(1,110)	(1,267)	(1,918)	(1,525)	(1,930)
Urban	0.75	0.73	0.75	0.80	0.71	0.81	0.73	0.75	0.73
	(0.43)	(0.45)	(0.43)	(0.40)	(0.46)	(0.40)	(0.45)	(0.44)	(0.44)

(Table 2.1 Continued)

Variables	All Mothers			Single Mother Sample			Married Mother Sample		
	Entire Sample	Displaced	Non-Displaced	Entire Sample	Displaced	Non-Displaced	Entire Sample	Displaced	Non-Displaced
High School or Less	0.50	0.73	0.49	0.59	0.78	0.58	0.46	0.69	0.45
	(0.50)	(0.45)	(0.50)	(0.49)	(0.42)	(0.49)	(0.50)	(0.46)	(0.50)
Age at Birth	26.07	24.62	26.14	25.14	24.14	25.22	26.46	24.95	26.52
	(4.45)	(4.47)	(4.44)	(4.65)	(4.72)	(4.63)	(4.31)	(4.27)	(4.30)
Single	0.30	0.42	0.29	-	-	-	-	-	-
	(0.46)	(0.49)	(0.45)	-	-	-	-	-	-

Note: Standard errors are in parentheses. The sample consists of children who are between the ages of 5 to 14, living with the mother at the time of the interview and have a test score. In addition, children whose mother does not satisfy displaced and non-displaced sample criteria are excluded. (1) The sample consists of children who are between the ages of 5 to 12. (2) The real income with base year 2000.

sample, seven-percent of the children have a displaced mother (lost her job involuntarily), which is higher compared to married mother sample in which only four-percent of the children have a displaced mother.

On average, in both single and married mother samples, forty-four-percent of children who have a displaced mother are first born. Thirty three-percent of children in single mother sample and sixty-one-percent of children in married mother sample are white. The number of siblings is similar for both samples, and the percentage of children with a displaced mother in public school for the single mother sample is higher. The behavioral problems index (BPI) is higher for single mother sample compared to married mother sample. The children with a displaced mother in the single mother sample are more antisocial, depressed, hyperactive and dependent compared to children in married mother sample.

Family income is expressed in real dollars (2000 prices) and is a monthly measure. Average family income is lower for single mother sample and mother income is the same for the single and the married mother samples. Other family income, non-mother income,[14] is lower for single mothers, which is expected since there is no husband to support the mother. Other income might be obtained from welfare payments, child support and other sources such as other family members. For the married mother sample, non-mother income is greater than mother income. In both samples, the displaced mothers have lower earnings and lower family income. On average, seventy eight-percent of children with a displaced mother in the single mother sample have a mother who has no more than a high school education and this percentage is lower for married mother sample. In other words, mothers in the married mothers sample are more educated.

[14] The other family income includes income earned by husband, income of other family members, welfare payments, child support and income from sources other than family members.

2.4. RESULTS

2.4.1. Mother's Job Displacement and Child's Test Scores

The baseline estimation results from equation [5] are presented in Table 2.2. Columns 1 and 2 show that the displacement coefficient is small, negative and statistically significant for both math and reading test scores. This result suggests that there is evidence that mother's job displacement has a negative impact on child's test scores. To be specific, the reading score is about seventeen-percent and math test is ten-percent of a standard deviation lower for children of displaced mothers compared to children of non-displaced mothers. Table 2.2 indicates that child and family characteristics are important determinants of the child's achievement. The results are consistent with the previous studies examining the child's education performance.[15] On average, children with more siblings have relatively lower math and reading scores than children with fewer siblings. This might be due to the sharing of parental resources. As the number of siblings increases, the child has to share financial and time resources that a parent can devote to their children. If the child is the first born, the test scores are higher. The first child spends some time alone with parents as the receiver of all resources. Thus, it is possible for a firstborn to accumulate higher human capital compared to her/his siblings (See Behrman and Taubman, 1986; Black, Devereux, and Salvanes, 2005). Females have higher test scores compared to males in reading. White children have higher test scores compared to non-white children and children in the public schools have lower test scores compared to the children who are in private, religious, and other types of schools.

If the mother has a high school education or less, the test scores for her children are lower compared to the mothers who have higher education levels. This effect might be due to the better

[15] See Haveman and Wolfe (1995) for a review of determinants of child's educational attainments.

Table 2.2
The Impact of Mother's Job Displacement on PIAT Scores - All Mothers Sample

Dependent Variables: PIAT scores	PIAT-Math	PIAT-Reading
	(1)	(2)
Job Displacement within 24-Month Window	-1.537*	-2.549***
	(0.838)	(0.889)
Characteristics of Child		
Number of Siblings	-0.775**	-0.930**
	(0.315)	(0.366)
First Born	0.958**	2.441***
	(0.477)	(0.536)
White	5.988***	3.412***
	(0.565)	(0.615)
Female	-0.340	2.879***
	(0.434)	(0.477)
Public School	-1.590***	-2.296***
	(0.565)	(0.586)
Characteristics of Mother		
High School or Less	-2.919***	-2.833***
	(0.541)	(0.613)
Urban	0.414	0.492
	(0.515)	(0.575)
Age at Birth	0.249**	0.268**
	(0.114)	(0.135)
Single	-0.675	-0.616
	(0.649)	(0.786)
Non-Mother Income	0.684***	0.880***
	(0.224)	(0.248)
Year and Age Effects	Yes	Yes
Observations	6,055	6,055

Note: Robust, mother-clustered standard errors are in parentheses. * 10%, ** 5%, ***1%.

supervision abilities of an educated mother or her attitudes towards education. For example, Leibowitz (1974) states that the quality of time spent with children increases with the parents' education level. Mother's age at birth is an important determinant of child's achievement. Similar to the education level of the mother, age at birth may affect the supervision abilities. In addition, it is likely that children born at later ages will be planned. Thus, it is more likely that the woman would spend more resources on the child. The higher the mother's age at birth, the higher are the child's reading and math scores as compared to mothers who had the child at early ages. Residing in an urban area and being a single mother do not have significant effects on child's test scores. The non-mother income has positive impact on both test scores.[16]

A job displacement that occurs at different times prior to the child's test date might have different impacts. Thus, it is important to control for the timing of the displacement. For example, a mother's displacement that happened three months prior to the test date and a displacement that occurred twelve months prior to the test date might have different impacts on test scores. Furthermore, it is important to consider the length of the time the mother has spent jobless following her job displacement. To address these issues, I divided the 24-month period prior to child's test date into two 12-month fixed displacement windows, $k = \{(0-12), (13-24)\}$.[17] Three job displacement dummies are created to show the timing of the job displacement and the length of the unemployment spell following the job displacement. If the mother was displaced one year prior to the test date and experienced an unemployment spell of up to twelve months, the first job displacement dummy takes the value of one, ${D_{jt}}^{k=(0-12)} = 1$. In other words, this job displacement dummy consists of children whose mother experienced a period of unemployment due to job displacement up to 12 months prior to the test date. The second dummy takes the value of one if the mother was displaced two years prior to the test date and stayed unemployed for at least thirteen months, ${D_{jt}}^{k=(13-24)} = 1$. The third one takes the value of one if the mother was displaced two years prior to the test date and experienced an unemployment spell of up to twelve months. In this latter case, the mother's joblessness period occurred and ended at least thirteen months prior to the test date. Thus, the first job displacement

[16] Excluding non-mother income does not change the results presented in Table 2.2. The coefficients of job displacement increase to -1.47 and -2.46 for math and reading scores respectively. Thus, evidence suggests that non-mother income is not affected by the job displacement of the mother.
[17] The mean of the time interval between the mother's job displacement and the child's test date is twelve months.

dummy shows the impact of a short run job displacement while the second and the third dummies show the impact of a long run job displacement. The control group includes children whose mothers were working continuously for three years - including the year the child took the test.

The results are presented in Table 2.3. The impact of displacement on test scores is negative for math (column 1) and reading scores (column 2) in any window. However, the job displacement coefficients are not statistically significant for math test and statistically significant for reading score only in the short run. This negative impact of the mother's job loss may be due to a decrease in quality and quantity of time spent with children or decrease in income. Following the displacement, the family might suffer sudden decreases in income. This loss might reduce the immediate financial resources as well as resources which might be available in the following year for the children. However, at the same time, the family might adjust the income by working more to compensate for mother's job loss. This adjustment in the family resources may be the reason that mother's job displacement has no impact on test scores in the long run.

I re-do the analysis to see if the impact of the mother's job displacement on her child's test scores changes by mother's marital status. In the case of single mothers there is no husband to compensate for the income loss due to a job loss and there is no emotional support after a job loss. Thus, the impact of a job displacement on the family might be different compared to a married mother's job displacement. Table 2.4 shows the impact of job displacement on child's test scores for single and married mother samples. The results in Panel A suggest that for the single mother sample, math and reading test scores are lower for children of displaced mothers (Panel A1). When I control for the unemployment spell following a job displacement, results show that a job displacement which was followed by an up to 12 months unemployment spell in

Table 2.3
The Impact of Mother's Job Displacement followed by different Unemployment Spells on Child's PIAT Scores
All Mothers Sample

Dependent Variables: PIAT scores	PIAT- Math	PIAT-Reading	Children with Displaced Mothers %
	(1)	(2)	
Displacement 0-12 month before test date	-1.471	-2.792**	2.44
(Unemployment=0-12 months)	(1.158)	(1.205)	
Displacement 13-24 month before test date	-1.950	-1.533	1.49
(Unemployment=0-12 months)	(1.349)	(1.470)	
Displacement 13-24 month before test date	-0.449	-2.987	0.51
(Unemployment=13-24 months)	(3.116)	(3.205)	
Child and Mother Characteristics	Yes	Yes	
Year and Age Effects	Yes	Yes	
Observations	6,055	6,055	

Note: Robust, mother-clustered standard errors are in parentheses. The coefficients reported are the effects of the Mother's Job Displacement on the child's test scores. Child characteristics are whether child is first born, white, female, number of siblings and whether child attends to public school and mother characteristics are whether the mother has high school education or lower, whether mother resides in an urban area, mother's age at first birth and non-mother income. * 10%, ** 5%, ***1%.

Table 2.4
The Impact of the Mother's Job Displacement on PIAT Scores by Mother's Marital Status

Dependent Variables: PIAT scores	PIAT-Math	PIAT-Reading	Children with Displaced Mothers %
Panel A: Single Mothers (N=1,799)			
Panel A1: 24-Month Window			
Job Displacement within 24-Month Window	-3.106***	-3.474**	
	(1.113)	(1.460)	
Panel A2: Different Windows			
Displacement 0-12 month before test date	-2.891**	-4.221**	3.61
(Unemployment=0-12 months)	(1.391)	(1.793)	
Displacement 13-24 month before test date	-2.624	-0.368	2.17
(Unemployment=0-12 months)	(1.845)	(2.443)	
Displacement 13-24 month before test date	-5.352	-7.300*	0.89
(Unemployment=13-24 months)	(3.556)	(4.358)	
Panel B: Married Mothers (N=4,256)			
Panel B1: 24-Month Window			
Job Displacement within 24-Month Window	-0.088	-1.676	
	(1.173)	(1.128)	
Panel B2: Different Windows			
Displacement 0-12 month before test date	-0.102	-1.547	1.95
(Unemployment=0-12 months)	(1.739)	(1.622)	
Displacement 13-24 month before test date	-0.906	-1.971	1.20
(Unemployment=0-12 months)	(1.901)	(1.813)	
Displacement 13-24 month before test date	5.791	2.264	0.35
(Unemployment=13-24 months)	(4.388)	(4.057)	
Child and Mother Characteristics	Yes	Yes	
Year and Age Effects	Yes	Yes	

Note: Robust, mother-clustered standard errors are in parentheses. The coefficients reported are the effects of the Mother's Job Displacement on the child's test scores. Child characteristics are whether child is first born, white, female, number of siblings and whether child attends to public school and mother characteristics are whether the mother has high school education or lower, whether mother resides in an urban area, mother's age at first birth and non-mother income. * 10%, ** 5%, ***1%.

the first window has a negative impact on both math and reading scores and coefficients are statistically significant for both test scores in the single mother sample (Panel A2). In other words, job displacement affects reading and math test scores negatively in the short run. In addition, the reading score is lower if the unemployment following a job displacement lasted more than a year. For the married mother sample, the job displacement has a negative impact on both scores (Panel B1). Coefficients are statistically insignificant and are lower compared to single mother sample coefficients. A married and displaced mother might be spending more time with children and helping them out with schoolwork with less stress since they might have emotional and financial support of the husband, leading to a less stressful environment at home.

2.4.2. Causality

The negative association between mother's job displacement and children's test scores that is documented in the previous section is consistent with the hypothesis that involuntary job displacement of the mother affects the child's test scores negatively. In this study, as in the literature, I assume that plant closure is an exogenous event and that mother's characteristics are independent of her job displacement. However, this correlation might be due to unobserved mother and child characteristics such as ability or productivity. For instance, less productive or less educated mothers might have self-selected themselves into failing plants. In this section, I utilize three strategies to investigate whether the correlations documented in the previous section are causal. First, I check exogeneity of mother's job displacement by employing a job displacement that occurred after the child took the test. Second, I estimate equation [5] by adding child fixed effects into the specification. Last, I employ the strategy discussed in Oster (2015), selection on unobservable variables, as a robustness check.

2.4.2.1. Exogeneity of Mother's Job Displacement

The descriptive statistics show that displaced mothers are less educated and they give birth at younger ages. This could invalidate the exogeneity assumption of plant closures. In order to test the exogeneity of job loss due to plant closures, I estimate job displacement which occurred within a 24-month period *after* the interview date (future job loss) on mother characteristics which are measured at the interview date. I employ future job displacement and interview date characteristics to investigate whether pre-displacement characteristics influence the displacement event as shown in equation [6].

$$D_{j,t+1} = \alpha + \boldsymbol{Z_{jt}}\boldsymbol{\psi}' + \boldsymbol{Y_{jt}}\boldsymbol{\delta}' + \lambda_t + \boldsymbol{e_{jt}} \qquad \textbf{[6]}$$

The existence of an association would mean that the assumption of exogeneity is not valid. Table 2.5 presents the results of all, single and married mother samples that are obtained by estimating equation [6]. Although displaced mothers have different levels of education and age at birth compared to non-displaced mothers, impact of both variables are small and statistically insignificant as the rest of the control variables. Thus, the evidence shows that, for both single and married mother samples, mother characteristics do not explain job displacement of the mother. The evidence from this exogeneity tests shows that, for both single and married other samples, the job displacement of the mother due to plant closure may be an exogenous event.

2.4.2.2. Fixed Effects

It is possible that unobserved ability of the mother, which might be affecting job displacement probability, is correlated with the ability of the child. In such a case, unobserved

Table 2.5
Exogeneity Test

Dependent Variable: Job Displacement within 24-month period *after* interview date			
	All Mother Sample	Single Mother Sample	Married Mother Sample
Age	-0.003	-0.003	-0.003
	(0.004)	(0.003)	(0.006)
Age Square	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Mother Income	-0.003	-0.011	-0.001
	(0.003)	(0.010)	(0.001)
Non-Mother Income	0.001	0.002	0.000
	(0.001)	(0.001)	(0.000)
High School or Less	0.001	-0.003	0.003
	(0.001)	(0.003)	(0.002)
Urban	0.001	-0.002	0.002
	(0.002)	(0.007)	(0.001)
Age at Birth	0.000	0.000	-0.000
	(0.000)	(0.001)	(0.000)
White	0.001	0.002	0.001
	(0.002)	(0.003)	(0.002)
Single	0.004	-	-
	(0.004)	-	-
Number of Children	0.001	0.006	-0.001
	(0.002)	(0.006)	(0.001)
Observations	2,947	831	2,116
Year Effects	Yes	Yes	Yes

Note: Robust standard errors are in parentheses. * 10%, ** 5%, ***1%.

child characteristics will be associated with mother's job displacement. The results from equation [5] with child fixed effects are shown in Table 2.6. Similar to previous results, coefficients of job displacement for reading and math test scores are negative, but only the coefficient for the reading score is statistically significant in the single mother sample (see Panel A). If the mother gets displaced, the child's reading score decreases by thirteen-percent of a standard deviation. The results presented in Panel B, column (4) show that the impact of the job displacement on reading score seems to be working in the short run for the single mother sample.

Table 2.6
The Impact of the Mother's Job Displacement on PIAT Scores
Fixed Effects Estimates

Dependent Variables: PIAT scores	All Mother Sample		Single Mother Sample		Married Mother Sample	
	PIAT-Math	PIAT-Reading	PIAT-Math	PIAT-Reading	PIAT-Math	PIAT-Reading
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 24-Month Window						
Job Displacement within 24-Month Window	0.948	-0.800	-0.083	-1.917*	1.342	-0.523
	(0.637)	(0.620)	(0.952)	(1.014)	(0.873)	(0.781)
Panel B: Different Windows						
Displacement 0-12 month before test date	1.101	-1.725*	-0.729	-3.809***	1.627	-0.476
(Unemployment=0-12 months)	(0.983)	(0.960)	(1.086)	(1.467)	(1.411)	(1.193)
Displacement 13-24 month before test date	1.506	0.414	1.275	1.342	1.613	-1.162
(Unemployment=13-24 months)	(1.051)	(0.977)	(1.745)	(1.394)	(1.484)	(1.332)
Displacement 0-12 month before test date	-0.305	-0.255	-1.909	-4.979	0.771	2.337
(Unemployment=0-12 months)	(1.797)	(1.964)	(3.585)	(3.024)	(2.029)	(1.693)
Observations	4,834	4,834	1,344	1,344	3,490	3,490
Child and Mother Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year and Age Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust, mother-clustered standard errors are in parentheses. The coefficients reported are the effects of the Mother's Job Displacement on the child's test scores. Child characteristics are whether child is first born, white, female, number of siblings and whether child attends to public school and mother characteristics are whether the mother has high school education or lower, whether mother resides in an urban area, mother's age at first birth and non-mother income. * 10%, ** 5%, ***1%.

The coefficient of displacement for the math score is positive (Panel A, column 5) and the coefficient of reading score is negative (Panel A, column 6) for the married mothers sample. However, coefficients are statistically insignificant.

2.4.2.3. Selection on Observables

The third strategy is from Oster (2015), which can be used to check the robustness of results. Adding observable controls and analyzing the movements in the coefficient of the variable of interest is one alternative way to check the robustness of results to omitted variable bias. However, Oster (2015) argues that coefficient movements are not sufficient to calculate this bias. R-squared movements should also be considered. Although I control for observable factors, the estimates might still be biased due to unobserved child and mother characteristics.

To calculate the identified set, which would yield results as if the job displacement was randomized, first, an equation only with the variable of interest- job displacement of the mother- is estimated. The restricted coefficient and R-squared values are obtained from this estimation. Then, a second regression equation that includes all controls is estimated and unrestricted coefficient and R-squared values are obtained. Using these values and making an assumption on R-squared, which would be obtained if all unobservable variables were measured and included into the equation, and on the degree of proportionality, which measures the relative importance of unobservable variables, an identified set can be calculated. This set provides a range for the level of stability in non-randomized data if the treatment was assigned exogenously. When the inclusion of control variables moves the coefficient of interest towards zero, exclusion of zero implies that the results are robust.

The results from this strategy are presented in Table 2.7. The table shows identified sets for $\tilde{\delta} = 1$, which means that observable variables are at least as important as the unobservable variables, and for two different bounds on R_{max}: 1.5 $\tilde{R}$ and 2.2 $\tilde{R}$. Inclusion of control variables affects the magnitude of the mother's job displacement moving it the coefficients towards zero (columns 1 to 6) and all identified sets exclude zero regardless of the R_{max} boundary. For the single mother sample, the set is far from including zero. However, the identified set for PIAT-Math for married mothers include zero with 2.2 $\tilde{R}$ boundary on maximum R-squared. As Oster (2015) discusses, the 2.2 $\widetilde{R}$ cutoff might be too aggressive and a smaller R_{max} might be more appropriate to use. In that case, 1.5 $\tilde{R}$ cutoff can be used to analyze the robustness. However, for the married mother sample even this cutoff seems to be too aggressive. From this table, it can be concluded that the relationship is causal at least for single mother sample. These two strategies, adding child fixed effects and selection on observables suggest that results reported in the previous section are causal.

2.4.3. Discussion of Possible Channels

Given that there is evidence that mother's job displacement affects children's test scores, in this part, I investigate the possible channels through which job displacement might affect test scores. I focus on two possible channels: income and child's behavioral problems.

2.4.3.1. Impact of Mother's Job Displacement on Income

As mentioned before, one of the effects of job displacement is the reduction in income. Table 2.8 shows the impact of mother's job displacement on family income (from equation 3) and on its components. Panel A presents the results for single mother families. The mother

Table 2.7

Coefficients of Mother's Job Displacement in the Baseline and Controlled Estimation Equations and Identified Sets

The Treatment Variable: Mother's Job Displacement

	Entire Sample		Single Mothers		Married Mothers	
	PIAT-Math	PIAT-Reading	PIAT-Math	PIAT-Reading	PIAT-Math	PIAT-Reading
	1	2	3	4	5	6
Baseline Effect	-2.926	-3.855	-3.740	-3.709	-1.645	-3.293
	(0.753)	(0.807)	(1.170)	(1.317)	(0.968)	(1.017)
	{0.019}	{0.012}	{0.014}	{0.012}	{0.020}	{0.012}
Controlled Effect	-1.537	-2.549	-3.105	-3.473	-0.087	-1.676
	(0.754)	(0.813)	(1.174)	(1.334)	(0.981)	(1.038)
	{0.131}	{0.114}	{0.101}	{0.086}	{0.126}	{0.110}
Identified Set						
$\tilde{\delta} = 1, \mu = 1.5$	[-1.537, -0.721]	[-2.549, -1.821]	[-3.105,-2.738]	[-3.473,-3.335]	[-0.087, 0.845]	[-1.676, -0.764]
$\tilde{\delta} = 1, \mu = 2.2$	[-1.537, 0.420]	[-2.549, -0.802]	[-3.105, -2.223]	[-3.473,-3.140]	[-0.087,2.150]	[-1.676, 0.512]

Note: Standard errors are in parentheses. The coefficients reported are the effects of the Mother's Job Displacement on the child's test scores. R-Squared is reported in the braces. The baseline regressions include year, age and sex dummies only.

Table 2.8

The Effect of the Mother's Job Displacement on Income Items by Mother's Marital Status

Dependent Variables: Income Components	Monthly Log Mother Income	Monthly Log Non-Mother Income	Monthly Log Family Income
Panel A: Single Mothers (N=1,230)			
Panel A1: 24-Month Window			
Job Displacement within 24-Month Window	-0.480***	0.309*	-0.200***
	(0.092)	(0.161)	(0.064)
Panel A2: Different Windows			
Displacement 0-12 month before test date	-0.619***	0.485**	-0.220**
(Unemployment=0-12 months)	(0.142)	(0.226)	(0.096)
Displacement 13-24 month before test date	-0.398***	0.176	-0.264**
(Unemployment=0-12 months)	(0.152)	(0.225)	(0.111)
Displacement 13-24 month before test date	-0.258	0.711**	0.043
(Unemployment=13-24 months)	(0.168)	(0.347)	(0.117)
Panel B: Married Mothers (N=2,777)			
Panel B1: 24-Month Window			
Job Displacement within 24-Month Window	-0.452***	-0.054	-0.195***
	(0.086)	(0.075)	(0.044)
Panel B2: Different Windows			
Displacement 0-12 month before test date	-0.343***	-0.053	-0.203***
(Unemployment=0-12 months)	(0.091)	(0.089)	(0.063)
Displacement 13-24 month before test date	-0.316***	-0.076	-0.201***
(Unemployment=0-12 months)	(0.095)	(0.133)	(0.072)
Displacement 13-24 month before test date	-0.761	-0.499	-0.303
(Unemployment=13-24 months)	(0.496)	(0.486)	(0.224)
Mother Characteristics and Year Effects	Yes	Yes	Yes

Note: Robust standard errors are in parentheses. The coefficients reported are the effects of the Mother's Job Displacement on income. Mother Characteristics are mother's age, age square, race of the mother, whether the mother has high school education or lower, whether mother resides in an urban area, mother's age at first birth and number of children. * 10%, ** 5%, ***1%.

income is forty-eight-percent and family income is twenty-percent lower for displaced mothers compared to mothers who were not displaced (Panel A1). Non-mother income is thirty-one-percent higher for displaced mothers and the coefficient is statistically significant. This evidence suggests that there is a support coming from other family members or other sources for single mothers. It might be due to possible welfare payments, food stamps, etc. an unemployed single mother can obtain. In addition, for single mothers, motivation to find a new job to compensate for income loss, which cannot be compensated by a husband, might be stronger compared to married mothers.

Panel B shows the impact of job displacement on income for the married mother sample. In married mother sample, displacement lowers mother income by approximately forty-five-percent (Panel B1). The impact of the job displacement in the long run is greater than the unemployment in the short run. It might be the case that married mothers give up looking for a job since there might be compensation for some of the mother income loss. It is possible that after the mother is displaced, other family members might choose to work more to compensate for income loss. However, I cannot find evidence supporting it. The family income is twenty-percent lower for displaced mothers in both samples. It decreases less than the decrease in mother income for both samples suggesting that there is some support coming from other family members, husband or the government, although I cannot find evidence supporting this claim for the married mother sample. The negative impact of job displacement on income that is reported here is consistent with the previous studies.

2.4.3.2. Impact of Mother's Job Displacement on Child's Behavioral Problems

Another possible channel is behavioral problems of children. Behavioral Problems Index (BPI) is based on twenty eight questions which were asked to mothers in each survey year. These questions are designed to measure the frequency, range and type of childhood behavioral problems for children age four and over in the past three months (NLSY Child Handbook, 1993) For each question, mothers are asked to choose whether the statement is often true (1), sometimes true (2) and not true (3). If the response is often or sometimes true the record takes the value of one and zero otherwise. Then these mother-reported responses are summed to create an overall BPI score. A higher BPI score represents a higher level of behavioral problems. There are six behavioral subscales created from these questions. These are antisocial, anxious/depressed, headstrong, hyperactive, immature dependency and peer conflict subscales.[18] The BPI overall score and each subscales are standardized measures with mean of 100 and standard deviation of 15. Similarly, the higher scores represent higher behavioral problems for each subscale.

Table 2.9.A shows the results of the analysis of the link between job displacement and child's behavioral problems by estimating equation [4] for the single mother sample only. Since the standard score is available only for the children of age 5 to 12, children aged 13 and 14 are not in the sample. The results at Panel A suggest that the overall BPI score is approximately twenty-eight-percent of a standard deviation higher for children of displaced mothers compared to children of mothers who were not displaced. It might be due to change in home-environment, increase in stress and depression of mother or depreciation in the quality of time the mother spends with children. There might be no other family member to support the mother emotionally,

[18] Questions related to each subscale are presented in Table A.2 in Appendix A.

Table 2.9.A
The Impact of the Mother's Job Displacement on Child's Behavioral Problems
Single Mothers

Dependent Variables: Behavioral Problems	BPI Score	Anti-social	Anxiety/ Depression	Headstrong	Hyperactive	Dependent	Peer Conflict
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: 24-Month Window							
Job Displacement within 24-Month Window	4.139**	2.726*	3.886**	2.052	2.960*	2.770*	2.588
	(1.776)	(1.594)	(1.634)	(1.558)	(1.759)	(1.650)	(1.731)
Panel B: Different Windows							
Displacement 0-12 month before test date	4.068	3.183	3.347	1.624	2.780	3.434	3.400
(Unemployment=0-12 months)	(2.582)	(2.050)	(2.434)	(2.306)	(2.455)	(2.130)	(2.407)
Displacement 13-24 month before test date	5.186**	5.532*	5.365**	4.294*	0.350	1.024	2.025
(Unemployment=0-12 months)	(2.605)	(2.981)	(2.595)	(2.304)	(2.450)	(3.177)	(2.771)
Displacement 13-24 month before test date	7.401	2.901	6.629***	1.644	8.675*	8.078**	2.888
(Unemployment=13-24 months)	(4.575)	(4.459)	(2.196)	(3.748)	(4.725)	(3.970)	(4.912)
Observations	1,191	1,191	1,191	1,191	1,191	1,191	1,191
Child and Mother Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and Age Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust, mother-clustered standard errors are in parentheses. The coefficients reported are the effects of the Mother's Job Displacement on child's behavioral problems. Child characteristics are whether child is first born, white, female, number of siblings and whether child attends to public school and mother characteristics are whether the mother has high school education or lower, whether mother resides in an urban area, mother's age at first birth and non-mother income. Children are at the ages of 5 to 12. * 10%, ** 5%, ***1%.

thus the stress might be spreading to children. As a result, children of single displaced mothers might be absorbing the stress and emotional problems of the mother and reflecting these problems at home and school. The child may become more antisocial, treat other kids at school badly to release the stress overload, try to hurt others to get attention, etc. The child might get fearful about the future, feel unhappy because of the problems at home, have sudden changes in the mood and have difficulties concentrating on school work. S/he might become more dependent to the mother trying to get her attention, become more disobedient and nervous at home.

When I examine the impact of mother's job displacement on the six subscales of behavioral problems measuring different aspects of behavioral problems, results suggest that children of displaced mothers are more antisocial, feel depressed, more hyperactive and more dependent compared to children of non-displaced mothers. To be specific, anti-social score is eighteen-percent, anxiety/depression score is twenty-six-percent, hyperactive score is twenty-percent and dependent score is eighteen-percent of a standard deviation higher for the children of displaced mothers compared to children of mothers who were not displaced. The coefficient of the short run job displacement is positive for all subscales, but statistically insignificant in all cases. The coefficients of the long run job displacement are also positive in all cases, representing a greater behavioral problem, and coefficients are statistically significant for all subscales (Panel B). The evidence suggests the longer the unemployment spell is, the greater the negative impact of mother's job displacement on behavioral problems. There is no evidence that mother's job displacement impacts child's behavioral problems for the married mother sample (Table 2.9.B). However, results presented in Panel B suggest that a married mother's involuntary job loss decreases behavioral problems of her child in the short-run.

Table 2.9.B
The Impact of the Mother's Job Displacement on Child's Behavioral Problems
Married Mothers

Dependent Variables: Behavioral Problems	BPI Score	Anti-social	Anxiety/ Depression	Headstrong	Hyperactive	Dependent	Peer Conflict
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: 24-Month Window							
Job Displacement within 24-Month Window	-0.976	-1.323	0.065	-0.804	-1.504	1.508	-0.707
	(1.572)	(1.443)	(1.266)	(1.323)	(1.247)	(1.434)	(1.054)
Panel B: Different Windows							
Displacement 0-12 month before test date *(Unemployment=0-12 months)*	-4.600**	-4.059**	-1.193	-3.493*	-3.312*	-1.715	-3.057***
	(2.178)	(1.742)	(1.735)	(1.845)	(1.742)	(1.991)	(1.005)
Displacement 13-24 month before test date *(Unemployment=0-12 months)*	3.876	1.048	3.791*	2.418	1.275	6.017**	1.492
	(2.375)	(2.603)	(2.012)	(2.222)	(2.051)	(2.429)	(1.999)
Displacement 13-24 month before test date *(Unemployment=13-24 months)*	0.414	1.149	-2.182	-2.586	-0.697	5.197**	-1.504
	(3.307)	(4.206)	(3.320)	(3.271)	(3.510)	(2.153)	(2.436)
Observations	3,016	3,016	3,016	3,016	3,016	3,016	3,016
Child and Mother Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and Age Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust, mother-clustered standard errors are in parentheses. The coefficients reported are the effects of the Mother's Job Displacement on child's behavioral problems. Child characteristics are whether child is first born, white, female, number of siblings and whether child attends to public school and mother characteristics are whether the mother has high school education or lower, whether mother resides in an urban area, mother's age at first birth and non-mother income. Children are at the ages of 5 to 12. * 10%, ** 5%, ***1%.

2.4.3.3. Are Income and Child's Behavioral Problems Channels Explaining the Impact of Job Displacement on Test Scores?

Previous sections have shown that mother's job displacement has a negative impact on family income and also on the child's behavioral problems. To investigate whether income and behavioral problems are channels through which job displacement affects child's test scores I include mother income and overall BPI score one at a time to the equation [5].

If income is a channel through which mother's job displacement affects child's test scores, adding mother income into equation [5] should alter the coefficient of job displacement. Results for single mother sample are presented in Table 2.10.A. The first two columns do not control for mother income or overall BPI score. Panel A, columns (3) and (4) show that after controlling for the mother income, the magnitude of the impact of job displacement decreases for both test scores, suggesting that mother's income is a channel through which mother's job displacement affects the child's test scores. The result is the same for short run and long run job displacements. The coefficient of the short run job displacement, a job displacement which is followed by up to twelve months unemployment spell, decreases for both scores and becomes statistically insignificant for math score (Panel B). These results support the evidence that income is a channel through which mother's job displacement affects test scores. This channel seems to be working in the short run since the coefficient of the long run job displacement slightly changes for both test scores after controlling for the mother income. Single mother's income and also family income decreases due to the job displacement. Hence, the effect of job displacement on mother income might be spreading to children outcomes.

Columns (5) and (6) present the results obtained from estimating equation [5] after controlling for both mother income and overall BPI score. The coefficient of job displacement decreases for both math and reading scores and becomes statistically insignificant for both scores

Table 2.10.A
The Impact of the Mother's Job Displacement on PIAT Scores:
The Role of Income and Child's Behavioral Problems
Single Mothers

Dependent Variables: PIAT scores	PIAT-Math	PIAT-Reading	PIAT-Math	PIAT-Reading	PIAT-Math	PIAT-Reading
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 24-Month Window						
Job Displacement within 24-Month Window	-3.116***	-3.469**	-2.337**	-2.883*	-2.248	-1.906
	(1.113)	(1.459)	(1.167)	(1.555)	(1.414)	(1.715)
Panel B: Different Windows						
Displacement 0-12 month before test date	-2.902**	-4.219**	-1.819	-3.422*	-1.742	-1.235
(Unemployment=0-12 months)	(1.390)	(1.792)	(1.506)	(1.932)	(1.715)	(2.181)
Displacement 13-24 month before test date	-2.638	-0.359	-2.124	0.018	-0.370	0.160
(Unemployment=0-12 months)	(1.845)	(2.442)	(1.860)	(2.454)	(2.593)	(2.498)
Displacement 13-24 month before test date	-5.362	-7.293*	-4.908	-6.959	-7.522*	-6.214
(Unemployment=13-24 months)	(3.554)	(4.358)	(3.533)	(4.422)	(3.840)	(4.532)
Observations	1,801	1,801	1,801	1,801	1,191	1,191
Mother Income	No	No	Yes	Yes	Yes	Yes
BPI Total Score	No	No	No	No	Yes	Yes
Child and Mother Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year and Age Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust, mother-clustered standard errors are in parentheses. The coefficients reported are the effects of the Mother's Job Displacement on child's test scores. Child characteristics are whether child is first born, white, female, number of siblings and whether child attends to public school and mother characteristics are whether the mother has high school education or lower, whether mother resides in an urban area, mother's age at first birth and non-mother income. * 10%, ** 5%, ***1%.

(Panel A). Specifically, the magnitude of the impact of job displacement decreases from twenty-one-percent to fifteen-percent of a standard deviation for math score and it decreases from twenty-three-percent to thirteen-percent of a standard deviation for the reading score after controlling for both mother income and overall BPI score. The results for married mother sample are shown in Table 2.10.B.

The results suggest that income and behavioral problems are channels explaining the link between the mother's job displacement and test scores. Since the sample size changes after controlling for BPI score, it is not possible to discuss which channel dominates the other. In other words, it is not clear whether the income effect is greater or lower compared to behavioral problems effect.

2.5. CONCLUSION

Using matched mother-child sample from the NLSY, I find evidence that the mother's job displacement has a negative impact on the child's test scores. The reading score is almost seventeen-percent lower for children of displaced mothers compared to children of mothers who were working continuously. The impact of job displacement on test scores is different for single and married mother samples. There is a negative impact of job displacement on child's both test scores for single mothers. After controlling for the length of unemployment spell followed by a job displacement, I find that there is a negative impact on math and reading scores in the short run for the single mother sample. The math score is nineteen-percent and reading score is twenty-eight-percent of a standard deviation lower for children of displaced mothers compared to children whose mothers were not displaced. There is no evidence that job displacement affects child's test scores for married mothers. Controlling for child fixed-effects, I find that estimated

Table 2.10.B
The Impact of the Mother's Job Displacement on PIAT Scores:
The Role of Income and Child's Behavioral Problems
Married Mothers

Dependent Variables: PIAT scores	PIAT-Math	PIAT-Reading	PIAT-Math	PIAT-Reading	PIAT-Math	PIAT-Reading
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 24-Month Window						
Job Displacement within 24-Month Window	-0.129	-1.702	0.216	-1.442	0.226	-1.084
	(1.162)	(1.116)	(1.161)	(1.114)	(1.398)	(1.327)
Panel B: Different Windows						
Displacement 0-12 month before test date	-0.163	-1.592	0.084	-1.400	-0.220	-1.587
(Unemployment=0-12 months)	(1.700)	(1.583)	(1.703)	(1.566)	(2.048)	(1.877)
Displacement 13-24 month before test date	-0.943	-1.988	-0.666	-1.772	0.511	-0.909
(Unemployment=0-12 months)	(1.902)	(1.814)	(1.876)	(1.812)	(2.191)	(2.142)
Displacement 13-24 month before test date	5.820	2.280	6.454	2.775	6.611	3.890
(Unemployment=13-24 months)	(4.423)	(4.079)	(4.009)	(3.895)	(4.111)	(3.775)
Observations	4,282	4,282	4,282	4,282	3,006	3,006
Mother Income	No	No	Yes	Yes	Yes	Yes
BPI Total Score	No	No	No	No	Yes	Yes
Child and Mother Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year and Age Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust, mother-clustered standard errors are in parentheses. The coefficients reported are the effects of the Mother's Job Displacement on child's test scores. Child characteristics are whether child is first born, white, female, number of siblings and whether child attends to public school and mother characteristics are whether the mother has high school education or lower, whether mother resides in an urban area, mother's age at first birth and non-mother income. * 10%, ** 5%, ***1%.

impact of displacement decreases for both test scores. The displacement coefficient is negative for both scores but only significant for the reading score. Falsification test suggest that plant closure may be an exogenous event and results from the Oster (2015)'s strategy show that results are causal.

I also examined whether income and child's behavioral problems are channels through which the job displacement might affect test scores. Job displacement of the mother has a negative effect on both family income and mother income and the child's behavioral problems for the single mother sample. To be able to investigate whether mother income and child's behavioral problems are channels which link mother's job displacement and child's test scores, mother income and overall BPI scores are added to the estimation equation for single mother sample. After adding mother income, coefficients of job displacement decrease for both test scores. Coefficients of short run and long run job displacements also decrease for both test scores and become statistically insignificant in the short run. After controlling for mother income and the overall BPI score, coefficients of job displacement decrease and become statistically insignificant for both test scores. The results suggest that mother income and child's behavioral problems are channels through which mother's job displacement affects math and reading test scores.

It can be concluded that child's test scores are affected by the mother's involuntary job loss. The negative impact of mother's job displacement on test scores seems to be working through income and child's behavioral problems channels. Contrary to Kalil and Ziol-Guest (2008) and Rege et al. (2011), I find evidence that mother's job displacement has an impact on child's educational achievement, which is measured by PIAT math and reading scores.

CHAPTER 3. IT PAYS OFF TO BE BLOND IN A NON-BLOND NEIGHBORHOOD: EYE COLOR, HAIR COLOR, ETHNIC COMPOSITION AND STARTING WAGES

3.1. INTRODUCTION

There is a long lasting interest in wage discrimination in the labor economics literature. Along with gender and race, physical attributes of an individual also might lead to wage discrimination. In recent years, there is an increasing attention to relationship between labor market outcomes and physical characteristics such as beauty, height, and obesity. Economic studies show that beauty is positively related to labor market outcomes of individuals (Hamermesh and Biddle, 1994; Biddle and Hamermesh, 1998; Harper, 2000; Mobius and Rosenblat, 2006; Robins, Homer and French, 2011). Hamermesh and Parker (2005) for the US and Süssmuth (2006) for Germany find that more attractive teachers receive higher instructional ratings, which would lead to higher salaries of instructors. In these studies, attractiveness is typically measured by ratings given by others, based on photographs or one's self-reported beauty ratings. There are some other physical characteristics that are utilized in the literature. Persico, Postlewaite and Silverman (2004) and Case and Paxon (2008) find that there is a wage premium for taller adults. Glied and Neidell (2010) show that teeth health, which is determined by exposure to fluoride, increases women's earnings by approximately four percent. Goldsmith, Hamilton and Darity (2007) find that white-black wage gap increases as skin color darkens. Hersch (2008) shows that, on average, new immigrants who have lighter skin color earn more compared to immigrants with darker skin color.

Eye and hair color also can be used to represent the looks of an individual; i.e. they can be used as dimensions of attractiveness. For example, having blue eyes and blonde hair represents a certain type of physical feature, which may be considered to be attractive. There are some studies particularly focusing on labor market outcomes of blonde women. Using NLSY79, Johnston (2010) finds that there is a wage premium for blonde women. In an experimental design where waitresses are asked to wear blonde, red and brown/dark colored wigs, Gueguen (2012) finds that waitresses with blonde wigs receive more tips from male customers. Price (2008) examines whether female fund-raisers' hair color affects fund raising success. He finds that blonde females raise more money compared to brunette fund-raisers.

There are several explanations of the wage premium due to physical attractiveness in economics and also psychology literature. In the economic theory, employer discrimination, consumer discrimination and occupational sorting provide explanation for the wage discrimination due to physical attractiveness. The employers might want to hire more attractive individuals based on two reasons: productivity expectations and taste based discrimination. They might assume that attractive individuals are more productive or they might simply prefer to work with attractive colleagues, which is a taste-based discrimination (Becker-type discrimination). Another explanation of attractiveness premium is consumer discrimination that stems from consumers' preference to interact with attractive workers. This type of discrimination might particularly be attributed to certain type of occupations that involves high volume of consumer-worker interactions (e.g. waitresses, salesman, etc.). Hamermesh and Biddle (1994) and Biddle and Hamermesh (1998); Glied and Neidell (2010) show some evidence of consumer, employer discrimination and occupational sorting.

There are two main groups of theories explaining the attractiveness effect in the psychology literature. These are the socialization and social expectancy theories and fitness-related evolutionary theories. The socialization theory states that appearance creates stereotypes, different expectations from attractive and unattractive individuals and different treatments towards them.[19] One can link worker attractiveness and employers' expectation of high productivity to social expectation theory. The roots of attractiveness effect start developing in the childhood. During childhood, attractive children might receive preferential treatment from teachers, parents or peers. It can be explained by fitness-related evolutionary theories that relate attractiveness with good-genes and differential parental treatment. Attractiveness, in this case, proxies health, quality and reproductive value. Thus, attractive children expected to be popular among their peers and teachers, and receive more parental investment due to their presumably high reproductive value. This differential treatment of attractive children might lead to developing higher cognitive and non-cognitive abilities such as test scores, confidence, personality, and social skills. Cognitive and non-cognitive skills contribute to human capital accumulation that, in return, is rewarded in the labor market (for example, Goldsmith, Veum and Darity, 1997; Heckman, Stixrud, and Urzua, 2006; Fortin, 2008; Drago, 2011).

There are several studies supporting the claim that attractiveness lead to higher human capital accumulation through behaviors and traits acquired due to attractiveness. Mobius and Rosenblat (2006) show that physically attractive workers are more confident and have better communication skills. Kuhn and Weinberger (2005) find that men who had leadership positions in high-school earn more as adults. In their study, Persico, Postlewaite and Silverman (2004), find evidence that premium due to being tall is stemming from social club associations in high school. Results in Case and Paxson (2008) show that height premium is the result of the correlation between height and cognitive ability. In addition, there is evidence that attractiveness increase academic performance (Cipriani and Zago, 2011; Von Bose, 2013; Deryugina and

[19] Psychology approaches to relationship between attractiveness and treatment by perceivers with general socialization/social expectancy theories and fitness related evolutionary theories. See Langlois, Kalalanis, Rubenstein, Larson, Hallam and Smoot (2000) for detailed discussion of these theories.

Shurchkov, 2015). Mocan and Tekin (2010) report a higher criminal propensity for less attractive individuals. They show that this result might be due to hindered human capital development in high school.

In this chapter, I investigate whether eye and hair color have an impact on wage-at-the first-job the individual holds after her/his schooling. The literature investigating the effect of beauty or physical attributes on labor market outcomes focuses on wages people earn in their mid-thirties or examines the impact of these attributes on wages for high school or college graduates only. The first-job wage does not include premiums due to the human capital accumulated due to job experiences and/or training opportunities on the job. If there is a wage premium due to attractiveness, it should be more appropriately observed with the first-job after schooling. Everything else held constant, two individuals with different physical characteristics, one attractive and other not, might start at the same position with different wages. In the beginning, employers might not be able to observe these two individuals' actual productivity. However, they might believe that attractive worker is more productive. In reality, unattractive individual might be more productive. In time, s/he might close the wage gap by performing better than the attractive colleague, by getting on the job trainings, or by seeking for other types of trainings more aggressively. Employing wage-at-the-first-job would eliminate the productivity gains obtained in the labor market.

I also investigate whether the wage premium due to eye color and hair color is still observed if the individual resides among people who have similar physical appearance. I assume that people of the same ethnic origin will have the same or similar physical attributes such as hair and eye color. For example, the hair and eye color of people of African, Hispanic and Asian descents are dark. However, people of European descents are more likely to have light-eye and hair color and a greater variation is expected among people of European descents. If the individual has similar characteristics with her/his own ethnic group, s/he might not be considered as attractive. For instance, a woman with blonde hair and blue/green eyes might be considered to be attractive in an area where Italian descendants are the majority of the population.[20] However, if this woman is of Scandinavian descent and residing in an area where Scandinavian descendants are the majority, she might not be considered as different or attractive since general population in that area is very likely to have similar attributes. Thus, the majority of one's own ethnic group in the area might matter. However, focusing only on whether one's own ethnic group constitutes the majority of a given area may not be the most appropriate measure to investigate the match between individual's attractiveness and county's eye/hair color attributes, which is the proxy for perception of attractiveness. One's own ethnic group might be a minority but other ethnic groups in the area might have the same or similar features in terms of eye and hair color. For example, those of German ethnic heritage might be in minority in a county. However, if people of Scandinavian descents are in the majority, the whole county will be identified by light-eye and light-hair color. In that case, although one's ethnic group is a minority, she might have the same attributes, eye and hair color, of the major ethnic group. In that case, having blue eyes and blonde hair might not be considered as different.

I utilize three anthropological studies (Coon, 1939; Hulse, 1963; and Geipel, 1969) to determine eye and hair color features of each ethnic group in a county. Based on the information obtained from these three sources, I classify each ethnic group as light-featured or dark-featured. If people of the ethnic group predominantly have blue/green eyes and blonde/red hair, that group

[20] Based on the hair and eye color maps provided in Coon (1939); Hulse (1963); and Geipel (1969), Italian population has darker features such as brown/black eye and brown/black hair color. In addition, Scandinavian people have light-eye and light-hair.

is defined as “light-featured”. If people of the ethnic group predominantly have drown/black hair and brown/black eyes, then that group is a “dark-featured” one. Then, based on the proportions of people of light-featured and dark-featured ethnic groups in the county, I obtain a measure for the eye/hair color composition of each county. If the share of people of light-featured ethnic groups is greater than fifty-percent, I define that county to be “light-featured” and if the share is less than or equal to fifty-percent, I classify the county as “dark-featured”.

Similarly, ethnic diversity is important in terms of how people perceive eye and hair color, or evaluate attractiveness. If the area in which the individual resides is very diverse in terms of ethnicity, the individual might be considered as attractive due to having light-eye and hair color because s/he might stand out in the crowd. However, it is also possible that in such an area, physical attributes might matter less because everybody has some degree of exoticism. If the individual lives in a neighborhood where ethnic diversity is low, people are more likely to have similar physical characteristics. In that case, an individual having the same hair/eye color as the rest of the population matters more.

There are studies investigating the impact of cultural and ethnic diversity on wages. Longhi (2013) investigates the impact of cultural diversity, measured by ethnic composition at the district level, on wages and job satisfaction and finds that people residing in more diverse districts earn more compared to those residing in less diverse areas. Ethnic diversity might increase the productivity due to different skill set provided by different ethnic groups, and hence higher wages. However, it is also possible that diversity might decrease productivity due to miscommunication, mismanagement, transaction costs and conflicts. For example, in a multi-national corporation context, Lazear (1999) discusses gains and costs of ethnic diversity. In a culturally diverse working place, workers can learn from one another when their information set (especially culture-specific) is different and when they have different but related skill sets. Then, one can expect that in such a working environment productivity should increase. However, if workers cannot understand each other, all the gains that can be obtained in the ethnically/culturally diverse environment become irrelevant. In order to keep the gain, the corporations have to bear communication costs, which means hiring bilingual workers and pay them higher wages. Alesina and La Ferrara (2005) show that ethnic diversity might lead to higher economic growth and productivity. On the other hand, Ottaviano and Peri (2005, 2006) show that cultural diversity has a net positive impact on average city wages and productivity. Different from these studies, this study contributes to the literature by analyzing the impact of ethnic diversity and eye/hair color composition of the county on starting wages of the individuals.

In this study, I find that having blonde/red hair generates four to six-percent point wage premium. The results are different for females and males. I find that having blonde/red hair has a positive impact on starting wages for females and white females. However, there is no evidence that hair color has an impact on starting wages for males. In addition, there is no evidence that eye color has an impact on starting wages of either females or males. Hair color, having blonde/red hair, still has a positive impact for females and white females after controlling for ethnic diversity. Ethnic diversity has a negative impact on wages of females, males and whites. In other words, as ethnic diversity increases, wages at the first-job increases. In order to investigate whether the positive impact of having blonde/red hair is still observed if the individual resides in a county where the majority of the population has similar features, I utilize detailed ethnic origin information collected in the census. In a dark-featured county, where people with brown/black hair are in majority, there is a wage premium for females with light-features (blonde/red hair) compared to females with dark-features (brown/black hair). For dark-featured individuals, there is a wage penalty for residing in a light-featured county, where people with blonde/red hair are in majority.

The eye/hair color composition of the “county” might be endogenous, potentially affected by unobservable individual, ethnic and location characteristics. Individual’s decision on where to reside might be affected by her personality, county and ethic characteristics. There might be some ethnic values taught to the individual that also might affect this decision. For example, some ethnicities might be more traditional and attribute high importance to the family ties leading the individual to reside in the area where she has many relatives. As a result, decision about where to reside might affect the wages and also the eye/color composition in the county. In that case, the coefficient estimates of the variable measuring the eye/hair color composition in the county would be biased. In order to determine whether results are causal, I follow two strategies. First, I employ the strategy in Oster (2015) where she introduces a strategy to check the robustness of results to omitted variable bias. Second, I use instrumental variables strategy and employ two instruments; state’s eye/hair color composition and the eye/color composition of the state based on the population under the age of 16. The results from these two strategies suggest that the relationship between color feature of the county and starting wages is causal.

The rest of the chapter proceeds as follows: Section 2 introduces the empirical specification, Section 3 is the data and the descriptive statistics, Section 4 presents the results and robustness checks, and last section concludes.

3.2. EMPIRICAL STRATEGY

To analyze the effect of eye and hair color on starting wage-at-the-first-job, I estimate the following regression equation:

$$lnW_i = \alpha_i + \boldsymbol{X_i\Omega}' + \beta_1 LightEye_i + \beta_2 LightHair_i + \lambda_i + \varepsilon_i \quad \textbf{[1]}$$

lnW_i is the log of the wage-at-the-first-job after schooling is completed. $LightEye_i$ is a dummy variable taking the value of one if the individual has blue, green, or hazel eyes (*light-eyes*) and takes the value of zero if s/he has brown or black eyes (*dark-eyes*). $LightHair_i$ is a dummy variable which takes the value of one if the individual has blond or red hair (*light-hair*) and zero if s/he has brown or black hair (*dark-hair*). X_i is the set of observable characteristics which includes age, gender, marital status, race and parental education. Race is controlled for in order to account for the fact that some races have less variety in hair and eye color. For example, there is more variation in hair color for whites compared to non-whites (African American, Asian or Hispanic). In order to control for different economic conditions and unobservable factors in job-start years, I include a set of first-job-start-year dummies, λ_i. Individuals have different starting years at the first-job ranging from 1979-1994.

Because an individual has no control over her/his "*natural*" eye and "*natural*" hair color, I consider these as exogenous characteristics that would help to identify a person's physical appearance. For instance, an individual with red hair and green eyes can be considered as attractive/different since s/he has distinctive physical characteristics which might not be very common. "*Natural*" eye and hair color do not change over time (at least between the ages of 16 to 30) and are independent of personal, family, region or interviewer attributes. For instance, education or income levels of one's parents, personality of the interviewer, unemployment rates in the county cannot alter "*natural*" hair or eye color of the individual. Throughout the study, I assume that individuals do not change their hair and eye color. It is possible that females with brown or black hair might dye their hair and change it to blonde, or individuals might wear green/blue contact lenses. This would introduce a measurement error in hair or eye color variable and lead to underestimation of the impact of having light-hair or having light-eyes. If the individual has blue/green/hazel eyes and/or blonde/red hair, s/he might be considered as attractive, hence gain a wage premium due to these features. In that case, β_1 and β_2 would be positive.

In order to investigate whether the proportion of individuals with light/dark-eyes and light/dark-hair in the county where the individual is residing affects the wage premium due to hair and eye color, I introduce a measure of eye/hair color composition of the county where the individual resides. $LightFC$ takes the value of one if the proportion of individuals of "light-featured" ethnic groups in the county is greater than fifty-percent. In order to examine if the impact of residing in a light or dark-featured county is different for individuals with blonde/red or brown/black hair I estimate the following regression equation:

$$lnW_i = a_i + \boldsymbol{X_i}\boldsymbol{\Gamma}' + \gamma LightEye_i + \theta_1 LightFC_{c,i} +$$

$$\theta_2 LightHair_i * LightFC_{\boldsymbol{c,i}} + \theta_3 LightHair_i * (1 - LightFC)_{\boldsymbol{c,i}} + \lambda_i + \varepsilon_i \qquad \textbf{[2]}$$

Having brown/black hair in a light-featured county might have positive or negate impact on wages. The individual might be treated as different in a discriminative sense, and be punished for not having the feature of the general population. In such a case, $\theta_1$is expected to be negative.

However, having a brown/black hair in that county might bring a wage premium (a positive sign on θ_1), if people of light-featured area consider having dark-features as attractive. In other words, θ_1 shows whether an individual with brown/black hair receives a premium among light-featured individuals, or whether she receives a penalty due to not residing in a dark-featured county where dark-featured individuals are in majority.

If the individual has blue/green/hazel eyes and blonde/red hair, s/he has light-features.[21] If s/he lives in an area where people of light-featured ethnicities are in majority, s/he might receive a wage premium compared to individuals with brown/black hair residing in the same area. This premium might be due to being similar to the majority of people. In that case, $\theta_2$becomes positive. However, she might not be considered as attractive in this area since the majority has light-features. In short, θ_2 shows the starting wage differences between individuals who have blonde/red hair and individuals with brown/black hair residing in a light-featured area. θ_3 shows the starting wage differences for individuals residing in a dark-featured area. A blonde person residing in a dark-featured area might stand out and receive a wage premium due to her different looks compared to an individual who has brown/black hair which is a common characteristic in this dark-featured area. In that case, $\theta_3$becomes positive.

3.3. DATA

I use two sources of data to analyze the effect of hair/eye color and the color feature of the region where the individual resides on the starting wage at the first-job an individual holds after completing schooling. The individual data are obtained from the National Longitudinal

[21] Although I cannot measure respondents' skin color in the data, in general light-eye and light-hair color are associated with lighter skin color (Coon, 1939).

Study of Youth (NLSY79) and county and state-level data are obtained from 1980 census of population.

3.3.1. National Longitudinal Study of Youth

NLSY79 includes 12,686 individuals, 6,403 males and 6,283 females, who were initially interviewed in 1979 and were 14-21 years of age as of December 1978. The NLSY79 was conducted annually from 1979 to 1994, and biennially thereafter. It provides information on demographic characteristics, work history, education status and the date education degree(s) obtained, and family characteristics such as parents' education status.

NLSY79 provides detailed employment information for the respondents. The work history file enables me to link jobs across years. Thus, I can accurately observe start/stop dates and measure duration of employment for each job held by each individual. The first-job is identified as the one the individual started after completing schooling, worked at least for two months and worked at least twenty hours a week. The latter two restrictions are required in order to get the first stable job.

In order to determine the first-job obtained after the schooling, I obtain the last date each individual was involved with school. If the s/he is a high school dropout, the last date of enrolment is counted as the last day of school. In addition, if the date of degree obtained or the date of last enrollment is missing, a date is assumed based on the enrollment status of the individual and months enrolled in school at each survey year. If the individual has a degree (high school, college, masters or higher) the date the highest degree obtained is the date schooling was completed. If s/he decides to pursue another degree and starts on that degree after two years obtaining the previous degree, the previous degree is employed as the date schooling was completed. For example, if the individual gets her/his high school diploma in May 1985 and starts college in August 1987, the last date the individual is involved in school is May 1985. During this two-year period, the individual might get a job, observe the labor market, and then decide to return to school based on the experience s/he obtains while working.

Additionally, the first-job is the one that starts within the first four-year period following schooling completion. For example, if the individual obtains her/his degree in May 1985, then the first-job should start by May 1989. In some cases the actual first-job cannot be observed due to missing information on hours worked and start/stop dates. This leads to a problem in determination of the first job. The four-year restriction reduces this problem. In addition, it drops individuals who decide to join in labor force many years after leaving school. Wages are expressed in real dollars (2000 prices).

In the 1985 survey of NLSY79, the individuals were asked about their "natural" eye and hair color.[22] Eye color ranges from light blue to black. If the individual has light blue, blue, green, hazel, or grey eyes,[23] s/he "has light-eyes" and if s/he has brown or black eyes, s/he has "dark-eyes". Hair color ranges from light blonde to black. If the individual has light blond, blond, red or grey hair, I consider this individual as having "light-hair". If s/he has brown or black hair, then s/he is considered as having "dark-hair".

3.3.2. Census of Population 1980

To measure ethnic diversity and to determine whether the individual resides among people of the same ethnic origin, county-level ancestry data from 1980 census of population are

[22] Out of 12,686 respondents, 10,876 of them replied to both of these questions by providing their natural hair and eye color, 2 of them refused to answer and 14 of them have invalid skip and there are 1,792 respondents who were not interviewed in 1985.
[23] I added respondents who chose "other" to this group.

employed. In the census, detailed ancestry information is collected from individuals. There is over a hundred of different ancestry groups recorded. By utilizing this ancestry information, I calculate two measures for each county. First, to measure the ethnic diversity in the area where NLSY respondents reside, I create Herfindahl-Hirsch Index (HHI) based on the reported ancestry groups in each county. HHI takes a value between zero and one. The value of one indicates that diversity is zero, the county is homogenous, and people residing in that particular county have the same ethnic origin. In other words, higher values of HHI imply lower ethnic diversity.

Second, I create a measure to determine eye/hair color composition of the county. If most of the people residing in the county have light-eyes and light-hair the county is defined as "*light-featured*". If most of the people in a county have "dark-eyes" and "dark-hair", it is a "*dark-featured*" county. However, eye and hair color information is not collected in the census, which makes it impossible to measure the exact share of people with light/dark-eyes and light/dark-hair. Thus, I use the proportion of people of light/dark-featured ethnic origins as a proxy for the eye/hair color composition of the county. I obtain this measure in two steps.

First, I determine eye/hair color feature of ethnic groups by utilizing three anthropological studies: Coon (1939), Hulse (1963) and Geipel (1969). These studies provide maps showing the distribution of light-eyes and light-hair in Europe and surrounding regions. By using these maps, I determine which ethnic groups have light-eyes and light-hair and which have dark-eyes and dark-hair. Hulse (1963) shows the percentage of light-hair and eyes on the map whilst Coon (1939) and Geipel (1969) classify different regions of Europe as light, almost even or dark-featured. Based on these studies, I define an ethnic group as "light-featured" if the percentage of people with light-hair and/or eye in the region is greater than fifty-percent according to Hulse's maps. If the percentage reported on maps is less than fifty-percent, then the ethnic group is counted as "dark-featured".[24] For example, in all these studies, the hair color and eye color are light at Scandinavia. To be specific, more than eighty-percent of the people of Scandinavia have light-eyes and light-hair. On the other hand, more than eighty-percent of the people of Italy have dark-eyes and dark-hair. Hence, the people of Italian heritage are counted as having dark-features whilst people who have Scandinavian origins counted as light-featured.

Once the eye/hair color feature of a particular ethnic group is determined, I use this information to proxy the eye/color feature of a county. Using 1980 census of population, I calculate the proportion of people of the light-featured ethnic groups and proportion of people of the dark-featured ethnic groups in each county based on the first ancestry reported. If the majority of people residing in the county are from light-featured ethnic origins, then this county is "light-featured" and if the majority has dark-featured ethnic origins the county is "dark-featured". For example, if the share of people of Scandinavian origins is greater than fifty-percent in the county, this county is a light-featured county.

3.3.3. Descriptive Statistics

Table 3.1 displays the descriptive statistics for the estimation sample.[25] The final estimation sample consists of 5,458 respondents, whose first-job information is not missing and have information on the control variables. The average wage at the first-job after schooling is twelve dollars. Half of the sample is female. Wage at the first-job is eleven dollars for females and it is almost thirteen dollars for males. For both males and female samples, the average age is about twenty.

[24] See Table B.1 for an example of ethnic groups that are defined as light-featured or dark-featured.

[25] See Table B.2 in Appendix B for definitions of variables.

Table 3.1
Descriptive Statistics

	All	Female	Male	White	White Female	White Male
Wage at the First-job	12.05	11.20	12.87	13.00	11.88	14.11
	(30.33)	(22.17)	(36.42)	(38.95)	(28.04)	(47.27)
Age	19.64	19.68	19.60	19.67	19.64	19.71
	(2.26)	(2.19)	(2.32)	(2.34)	(2.21)	(2.46)
White	0.60	0.61	0.59	-	-	-
	(0.49)	(0.49)	(0.49)	-	-	-
Female	0.49	-	-	0.50	-	-
	(0.50)	-	-	(0.50)	-	-
Light-Eyes	0.42	0.43	0.41	0.66	0.66	0.65
	(0.49)	(0.49)	(0.49)	(0.48)	(0.47)	(0.48)
Light-Hair	0.14	0.15	0.13	0.23	0.25	0.21
	(0.35)	(0.36)	(0.33)	(0.42)	(0.43)	(0.41)
Light-Eyes & Light-Hair	0.12	0.13	0.11	0.20	0.22	0.18
	(0.33)	(0.34)	(0.31)	(0.40)	(0.41)	(0.39)
Dark-Eyes & Light-Hair	0.02	0.02	0.02	0.03	0.03	0.03
	(0.14)	(0.14)	(0.13)	(0.16)	(0.17)	(0.16)
Light-Eyes & Dark-Hair	0.30	0.29	0.30	0.45	0.45	0.46
	(0.46)	(0.46)	(0.46)	(0.50)	(0.50)	(0.50)
Dark-Eyes & Dark-Hair	0.56	0.55	0.57	0.32	0.31	0.33
	(0.50)	(0.50)	(0.49)	(0.47)	(0.46)	(0.47)
Mother Less than High School	0.37	0.36	0.37	0.27	0.27	0.26
	(0.48)	(0.48)	(0.48)	(0.44)	(0.44)	(0.44)
Mother High School Graduate	0.39	0.41	0.38	0.47	0.47	0.47
	(0.49)	(0.49)	(0.49)	(0.50)	(0.50)	(0.50)
Mother College Graduate	0.16	0.16	0.16	0.20	0.20	0.20
	(0.37)	(0.37)	(0.36)	(0.40)	(0.40)	(0.40)
Mother Master’s Degree or more	0.02	0.02	0.02	0.03	0.03	0.03
	(0.15)	(0.15)	(0.15)	(0.17)	(0.17)	(0.16)
Father Less than High School	0.33	0.32	0.34	0.28	0.27	0.29
	(0.47)	(0.47)	(0.47)	(0.45)	(0.44)	(0.45)
Father High School Graduate	0.30	0.31	0.29	0.34	0.35	0.32
	(0.46)	(0.46)	(0.45)	(0.47)	(0.48)	(0.47)
Father College Graduate	0.18	0.18	0.17	0.23	0.23	0.23
	(0.38)	(0.38)	(0.38)	(0.42)	(0.42)	(0.42)
Father Master’s Degree or more	0.06	0.06	0.06	0.08	0.08	0.09
	(0.24)	(0.23)	(0.24)	(0.28)	(0.27)	(0.28)
Light-Featured County	0.52	0.53	0.52	0.69	0.69	0.69
	(0.49)	(0.49)	(0.49)	(0.46)	(0.46)	(0.46)
HHI	0.22	0.22	0.22	0.21	0.21	0.21
	(0.13)	(0.13)	(0.12)	(0.11)	(0.11)	(0.11)
Observations	5,458	2,662	2,796	3,254	1,613	1,641

Note: Standard Errors are in parentheses.

Forty-two-percent of the sample has blue/green/hazel eyes (light-eyes). Among these individuals twelve-percent have blonde/red hair and thirty-percent have brown/black hair. According to these numbers, having both blue/green/hazel eyes and blonde/red hair is not a common feature among NLSY79 respondents. However, having blue/green/hazel eyes for individuals with blonde/red is a common feature. Fourteen-percent of the sample has blonde or red hair. Among individuals with blonde/red hair twelve-percent of them have blue/green/hazel eyes. Fifty-six-percent of respondents have brown/black eyes and hair and it is thirty-two-percent for the whites. Education levels of respondents' parents are similar for female and male respondents and they are higher for white respondents.

Half of the individuals in the sample are residing in a light-featured county. Almost seventy-percent of the white sample resides in light-featured counties. Ethnic diversity, HHI, is 0.22, which implies that individuals in the sample are residing in relatively diverse counties. Figure 3.1 shows the color feature of counties in the US based on the share of ethnicities with light/dark-features.

Table 3.2.A shows descriptive statistics by eye and hair color groups. Respondents with blue/green/hazel eyes, on average approximately one dollar, compared to respondents with brown/black eyes. However, the difference is statistically insignificant. If the respondent has blonde/red hair s/he earns almost five dollars more compared to individuals with brown/black hair on average. It seems that, having blonde hair matters more compared to having blue/green/hazel eyes. If the individual has both blonde/red hair and blue/green/hazel eyes, on average s/he earns around fourteen dollars per hour. If s/he has brown/black eyes and hair, then s/he earns eleven dollars per hour. Thus, we can expect that having blue/green/hazel eyes and/or blonde/red hair might have an impact on the wage-at-the-first-job.

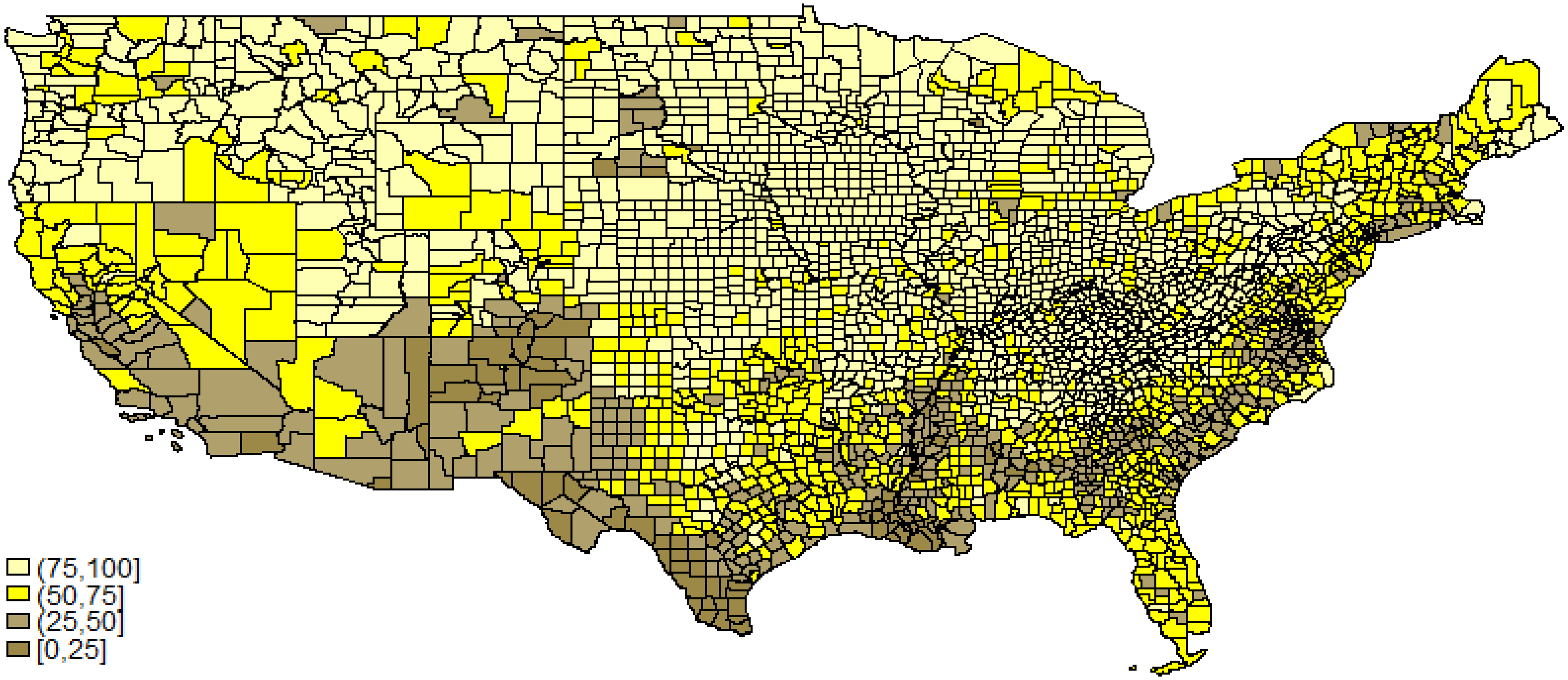

Figure 3.1
Color-Feature of Counties Based on the Share of Light/Dark-Featured Ethnicities

Note: Yellow shows light-featured counties while brown represents dark-featured counties. Light yellow represents counties where the share of light-featured ethnic groups is greater than seventy-five-percent. Dark brown shows the counties where share of light-featured ethnicities is less than twenty-five percent. Out of 52 states, 9 of them are determined as light-featured and 43 of them as dark-featured with fifty-percent threshold. With the seventy-five-percent threshold, the number of states that are light-featured increases to 22.

Table 3.2.A
Descriptive Statistics by Eye and Hair Color

	Eyes			Hair		
	Light-Eyes	Dark-Eyes		Light-Hair	Dark-Hair	
Wage at the First-job	12.47	11.75		16.24	11.37	***
	(22.83)	(34.71)		(7.78)	(8.74)	
Age	19.67	19.61		19.63	19.64	
	(2.35)	(2.19)		(2.23)	(2.26)	
White	0.94	0.35	***	0.97	0.54	***
	(0.24)	(0.48)		(0.17)	(0.50)	
Female	0.50	0.48		0.54	0.48	***
	(0.50)	(0.50)		(0.50)	(0.50)	
Light-Eyes	-	-		0.86	0.34	***
	-	-		(0.34)	(0.47)	
Dark-Eyes	-	-		0.14	0.66	
	-	-		(0.34)	(0.47)	
Light-Hair	0.29	0.03	***	-	-	
	(0.45)	(0.17)		-	-	
Dark-Hair	0.71	0.97		-	-	
	(0.45)	(0.17)		-	-	
Mother Less than High School	0.27	0.44	***	0.25	0.39	***
	(0.44)	(0.50)		(0.43)	(0.49)	
Mother High School Graduate	0.46	0.35	***	0.48	0.38	***
	(0.50)	(0.48)		(0.50)	(0.49)	
Mother College Graduate	0.20	0.13	***	0.21	0.15	***
	(0.40)	(0.33)		(0.40)	(0.36)	
Mother Master's Degree or more	0.03	0.02	***	0.03	0.02	
	(0.17)	(0.13)		(0.16)	(0.15)	
Father Less than High School	0.27	0.37	***	0.27	0.34	***
	(0.44)	(0.48)		(0.44)	(0.47)	
Father High School Graduate	0.33	0.28	***	0.35	0.29	***
	(0.47)	(0.45)		(0.48)	(0.45)	
Father College Graduate	0.24	0.13	***	0.21	0.17	***
	(0.42)	(0.34)		(0.41)	(0.38)	
Father Master's Degree or more	0.08	0.04	***	0.10	0.05	***
	(0.27)	(0.20)		(0.29)	(0.22)	
Light-Featured County	0.70	0.40	***	0.69	0.50	***
	(0.46)	(0.49)		(0.46)	(0.50)	
HHI	0.21	0.24	***	0.21	0.23	***
	(0.11)	(0.13)		(0.11)	(0.13)	
Observations	2,275	3,184		766	4,693	

Note: Standard Errors are in parentheses. Light-Eyes: Blue/Green/Hazel Eyes, Dark-Eyes: Brown/Black Eyes, Light-Hair: Blonde/Red Hair and Dark-Hair: Brown/Black Hair. The means are statistically different across the two groups at * 10%, ** 5%, or ***1%.

Table 3.2.B and Table 3.2.C show descriptive statistics by eye and hair color for females and males, respectively. Females with blue/green/hazel eyes earn almost two dollars more compared to females with brown/black eyes (Table 3.2.B). The difference is greater, and almost four dollars, for blonde/red hair females compared to females with brown/black hair. The wage at the first-job for males with light eyes and dark eyes is the same. However, blond/red hair males, on average, earn six dollars more compared to males with dark hair (Table 3.2.C). Having light features (eyes and hair) seems to matter for females, while for males, only having light hair matters.

3.4. RESULTS

The results obtained from equation [1] are presented in Table 3.3. Column (1) shows that, on average the starting wages of individuals with blonde/red hair are four-percent higher compared to individuals with brown/black hair. This result suggests that having blonde/red hair has a positive impact on starting wages. I find that the coefficient of having blonde/red hair is positive for both females and males. However, it is statistically significant, only for females. If a female has blonde/red hair, she earns six-percent wage premium at the starting job (column 2). Columns (4) to (6) show the impact of eye and hair color on starting wages for whites. Column (4) shows that white individuals with blonde/red hair earn four-percent more compared to whites with brown/black hair. The evidence of six-percent wage premium due to having blonde/red hair is consistent with the existing studies that find four to ten-percent wage premium for attractive individuals (Hamermesh and Biddle, 1994; Mobius and Rosenblat, 2006; Fletcher, 2009; Robins et al. 2011). In addition, this result is consistent with the Johnston (2010)'s finding that white and blonde women earn seven-percent more compared to

Table 3.2.B
Descriptive Statistics for Females by Eye and Hair Color

	Eyes			Hair		
	Light	Dark		Light	Dark	
Wage at the First-job	12.08	10.55	*	14.40	10.62	***
	(31.35)	(11.26)		(51.45)	(9.91)	
Age	19.67	19.69		19.58	19.70	
	(2.23)	(2.16)		(2.21)	(2.19)	
White	0.94	0.36	***	0.96	0.54	***
	(0.23)	(0.48)		(0.18)	(0.50)	
Light-Eyes	-	-		0.86	0.35	***
	-	-		(0.12)	(0.48)	
Dark-Eyes	-	-		0.14	0.65	***
	-	-		(0.12)	(0.48)	
Light-Hair	0.31	0.04	***	-	-	
	(0.46)	(0.19)		-	-	
Dark-Hair	0.69	0.96		-	-	
	(0.46)	(0.19)		-	-	
Mother Less than High School	0.26	0.44	***	0.24	0.39	***
	(0.44)	(0.50)		(0.18)	(0.49)	
Mother High School Graduate	0.46	0.36	***	0.51	0.39	***
	(0.50)	(0.48)		(0.25)	(0.49)	
Mother College Graduate	0.21	0.13	**	0.20	0.15	***
	(0.41)	(0.33)		(0.16)	(0.36)	
Mother Master's Degree or more	0.03	0.02	**	0.02	0.02	
	(0.17)	(0.13)		(0.02)	(0.15)	
Father Less than High School	0.26	0.37	***	0.26	0.34	***
	(0.44)	(0.48)		(0.19)	(0.47)	
Father High School Graduate	0.35	0.29	***	0.38	0.30	***
	(0.48)	(0.45)		(0.24)	(0.46)	
Father College Graduate	0.23	0.13	***	0.20	0.17	
	(0.42)	(0.34)		(0.16)	(0.38)	
Father Master's Degree or more	0.08	0.04	***	0.10	0.05	
	(0.27)	(0.20)		(0.09)	(0.22)	
Light-Featured County	0.70	0.40	***	0.71	0.50	***
	(0.46)	(0.49)		(0.21)	(0.50)	
HHI	0.16	0.18	***	0.16	0.17	**
	(0.08)	(0.12)		(0.01)	(0.11)	
Observations	1,134	1,528		410	2,252	

Note: Standard Errors are in parentheses. Light-Eyes: Blue/Green/Hazel Eyes, Dark-Eyes: Brown/Black Eyes, Light-Hair: Blonde/Red Hair and Dark-Hair: Brown/Black Hair. The means are statistically different across the two groups at * 10%, ** 5%, or ***1%.

Table 3.2.C
Descriptive Statistics for Males by Eye and Hair Color

	Eyes			Hair		
	Light	Dark		Light	Dark	
Wage at the First-job	12.86	12.87		18.35	12.07	***
	(7.91)	(46.89)		(10.18)	(7.43)	
Age	19.67	19.55		19.69	19.59	
	(2.47)	(2.22)		(2.26)	(2.34)	
White	0.93	0.35	***	0.97	0.53	***
	(0.25)	(0.48)		(0.17)	(0.50)	
Light-Eyes	-	-		0.87	0.34	***
	-	-		(0.34)	(0.47)	
Dark-Eyes	-	-		0.13	0.66	***
	-	-		(0.34)	(0.47)	
Light-Hair	0.27	0.03	***	-	-	
	(0.44)	(0.17)		-	-	
Dark-Hair	0.73	0.97		-	-	
	(0.44)	(0.17)		-	-	
Mother Less than High School	0.27	0.44	***	0.27	0.39	***
	(0.45)	(0.50)		(0.44)	(0.49)	
Mother High School Graduate	0.45	0.34	***	0.45	0.37	***
	(0.50)	(0.47)		(0.50)	(0.48)	
Mother College Graduate	0.20	0.13	***	0.21	0.15	***
	(0.40)	(0.33)		(0.41)	(0.36)	
Mother Master’s Degree or more	0.03	0.02		0.03	0.02	
	(0.17)	(0.14)		(0.17)	(0.15)	
Father Less than High School	0.28	0.38	***	0.28	0.35	***
	(0.45)	(0.48)		(0.45)	(0.48)	
Father High School Graduate	0.31	0.27	**	0.32	0.28	
	(0.46)	(0.44)		(0.47)	(0.45)	
Father College Graduate	0.24	0.13	***	0.22	0.17	***
	(0.43)	(0.34)		(0.42)	(0.37)	
Father Master’s Degree or more	0.08	0.04	***	0.10	0.05	***
	(0.28)	(0.21)		(0.29)	(0.23)	
Light-Featured County	0.69	0.40	***	0.68	0.49	***
	(0.46)	(0.49)		(0.47)	(0.50)	
HHI	0.16	0.18	***	0.16	0.17	**
	(0.08)	(0.11)		(0.08)	(0.10)	
Observations	1,141	1,656		356	2,441	

Note: Standard Errors are in parentheses. Light-Eyes: Blue/Green/Hazel Eyes, Dark-Eyes: Brown/Black Eyes, Light-Hair: Blonde/Red Hair and Dark-Hair: Brown/Black Hair. The means are statistically different across the two groups at * 10%, ** 5%, or ***1%.

Table 3.3

Impact of Eye and Hair Color on Wages at the First-job

Dependent Variable: Wages at the First-job	All	Female	Male	White	White Female	White Male
	1	2	3	4	5	6
Blue-Green-Hazel Eye	0.004	-0.002	0.006	-0.005	-0.018	0.001
	(0.018)	(0.025)	(0.026)	(0.020)	(0.027)	(0.029)
Blond-Red Hair	0.043**	0.055*	0.032	0.044**	0.058*	0.028
	(0.021)	(0.030)	(0.031)	(0.022)	(0.031)	(0.032)
Female	-0.150***	-	-	-0.156***	-	-
	(0.013)	-	-	(0.018)	-	-
White	0.041**	0.027	0.056**	-	-	-
	(0.019)	(0.026)	(0.026)	-	-	-
Single	0.135***	0.178***	-0.075	0.151**	0.191**	-0.144
	(0.050)	(0.058)	(0.078)	(0.071)	(0.078)	(0.125)
Age	0.083*	0.047	0.093	0.122**	0.044	0.132*
	(0.049)	(0.084)	(0.059)	(0.058)	(0.102)	(0.071)
Age Square	-0.001	0.000	-0.001	-0.002	0.001	-0.002
	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)
Father						
High School Graduate	0.016	0.011	0.019	0.013	-0.018	0.042
	(0.016)	(0.024)	(0.021)	(0.021)	(0.030)	(0.029)
College Graduate	0.048**	0.047	0.052*	0.052*	0.039	0.067*
	(0.022)	(0.032)	(0.029)	(0.027)	(0.039)	(0.037)
Master’s Degree or more	0.069*	0.094	0.053	0.051	0.065	0.034
	(0.038)	(0.061)	(0.043)	(0.044)	(0.072)	(0.051)
Mother						
High School Graduate	0.068***	0.056**	0.080***	0.083***	0.109***	0.057**
	(0.016)	(0.024)	(0.022)	(0.021)	(0.032)	(0.029)
College Graduate	0.090***	0.148***	0.036	0.102***	0.184***	0.026
	(0.024)	(0.036)	(0.032)	(0.031)	(0.047)	(0.040)
Master’s Degree or more	0.101**	0.112*	0.097	0.125**	0.120*	0.135
	(0.045)	(0.060)	(0.064)	(0.056)	(0.073)	(0.085)
First-job Start Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,458	2,662	2,796	3,254	1,613	1,641
R-Square	0.23	0.21	0.23	0.26	0.24	0.25

Note: Standard errors are clustered at the state-county-year-level. Dependent variable is hourly real wage in cents in 2000 prices. The first-job is the one in which respondent worked more than two months and for more than twenty hours in a week after completing the schooling. For parents’ education, being high school dropout is the control group. * 10%, ** 5%, ***1%.

white brunettes. The coefficient of having blonde/red hair is positive for males (columns 3 and 6), however it is statistically insignificant.

The coefficient of having blue/green/hazel eyes has mixed sign for different sample groups. It is positive for males (columns 3 and 6) and negative for females (columns 2 and 5). However, it is statistically insignificant for both males and females. Thus, while there is no evidence that eye and hair color have an impact on starting wages for males, hair color has impact on wages for females. Whites earn almost four and a half-percentage point more compared to non-whites.[26] Females earn fifteen-percent less compared to males. These results are consistent with the previous studies investigating white and non-white and female-male wage gaps.[27] Additionally, individuals with more educated parents earn more. More educated parents might be more able to help with schooling at early ages, motivate for higher level of education and assign stronger importance to education.

Table 3.4.A presents the results from equation [2]. Ethnic diversity measure, HHI, has a negative sign and statistically significant for all samples. As HHI increases (ethnic diversity decreases), wage-at-the-first-job decreases. In other words, there is a positive relationship between wages and ethnic diversity. The result is consistent with the previous studies (Longhi, 2013; Ottaviano and Peri, 2005 and 2006). In terms of magnitude, if a county goes from perfect heterogeneity (HHI=0) to perfect homogeneity (HHI=1), that would decrease the wages by twenty-five-percent to thirty-five-percent (columns 1-6).

If the individual has dark-features and residing in a light-featured county, she might be considered as different/attractive and earn a wage premium. On the other hand, if there is a preference for light-featured individuals, then she might receive a wage penalty. The results in

[26] Non-white group consists of African American, Asian and Hispanic origins.
[27] See Altonji and Blank (1999)

Table 3.4.A
Impact of Hair Color and Color Feature of the County on Wages at the First-job
Share of Light-Featured Ethnicities>50%

Dependent Variable: Wages at the First-job						
	All	Female	Male	White	White Female	White Male
	1	2	3	4	5	6
Light Eyes	0.009	-0.008	0.021	-0.000	-0.029	0.023
	(0.019)	(0.024)	(0.029)	(0.021)	(0.027)	(0.034)
HHI(1)	-0.256***	-0.286***	-0.236***	-0.271***	-0.348***	-0.215*
	(0.056)	(0.082)	(0.076)	(0.087)	(0.126)	(0.119)
Light-FC (2)	-0.051***	-0.054**	-0.044*	-0.057**	-0.036	-0.073**
	(0.018)	(0.025)	(0.025)	(0.023)	(0.032)	(0.033)
Light Hair * Light-FC	0.046	0.073	0.017	0.046	0.056	0.027
	(0.034)	(0.047)	(0.052)	(0.035)	(0.047)	(0.053)
Light Hair * (1-Light-FC)	0.050*	0.044	0.059	0.054*	0.069	0.038
	(0.030)	(0.042)	(0.039)	(0.032)	(0.045)	(0.043)
All Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
First-job Start Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,875	2,400	2,475	2,742	1,379	1,363
R-Square	0.23	0.22	0.23	0.27	0.26	0.27

Note: Standard errors are clustered at the state-county-year level. Dependent variable is hourly real wage in cents in 2000 prices. The first-job is the one in which respondent worked more than two months and for more than twenty hours in a week after completing the schooling. For parents' education, being high school dropout is the control group. Other control variables are gender, race, age and parents' education. * 10%, ** 5%, ***1%. (1) HHI is the measure of ethnic diversity. Higher values of HHI mean less diversity. (2) Light-FC takes the value of one if the share of people of light-featured ethnic origins is greater than fifty-percent. The reference group is dark-featured individuals residing in dark-featured counties.

Table 3.4.A, column (1), support the latter hypothesis. Among individuals with brown/black hair, the ones residing in light-featured counties earn five-percent less compared to their counterparts residing in dark-featured areas (column 1). This result suggests that there is a wage penalty for individuals with brown/black hair residing in light-featured counties.

If the individual has light-features and resides in a light-featured county, it is possible that she might not be considered as attractive since people in that county are likely to have this feature. On the other hand, she might earn more compared to the ones who have dark-features if people still have a preference for light-featured individuals. Table 3.4.A, column (1) supports the latter hypothesis. Among individuals residing in light-featured counties, the ones with blonde/red hair earn almost five-percent more compared to individuals with brown/black hair. However, it is not statistically significant.

A blonde individual might stand out in a dark-featured county and gain a wage premium due to her different looks. The coefficient for the interaction between light hair and dark-featured county is positive (column1). It implies that an individual with blonde/red hair and residing in dark-featured county earns five-percent more, compared to an individual with brown/black hair residing in the same county. The impact seems to be coming from the white individuals. In a dark-featured county blonde/red hair whites earn five-percent more compared to brown/black hair females (column 4). The results suggest that there is a wage premium for blonde whites.

Table 3.4.B shows the results from equation [2] with state fixed effects. The ethnic diversity coefficient is still negative and statistically significant for the entire sample and males only (columns 1 and 3). The evidence suggests that ethnic diversity of the county has no impact on the wage-at-the-first-job for females and whites residing in the same state. The wage is not different for the brown/black hair individuals residing in dark-featured counties and their

Table 3.4.B
Impact of Hair Color and Color Feature of the County on Wages at the First-job
Share of Light-Featured Ethnicities>50%
with State Fixed Effects

Dependent Variable: Wages at the First-job						
	All	Female	Male	White	White Female	White Male
	1	2	3	4	5	6
Light Eyes	0.013	0.000	0.019	0.010	-0.015	0.026
	(0.019)	(0.025)	(0.030)	(0.022)	(0.028)	(0.035)
HHI (1)	-0.144**	-0.043	-0.251***	-0.130	-0.100	-0.128
	(0.071)	(0.114)	(0.085)	(0.103)	(0.155)	(0.125)
Light-FC (2)	-0.006	-0.018	0.012	-0.035	-0.055	-0.017
	(0.023)	(0.035)	(0.031)	(0.030)	(0.044)	(0.042)
Light Hair * Light-FC	0.040	0.053	0.011	0.044	0.044	0.017
	(0.034)	(0.047)	(0.052)	(0.036)	(0.048)	(0.054)
Light Hair * (1-Light-FC)	0.052*	0.062	0.051	0.057*	0.082*	0.035
	(0.030)	(0.042)	(0.039)	(0.032)	(0.045)	(0.044)
All Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
First-job Start Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,875	2,400	2,475	2,742	1,379	1,339
R-Square	0.25	0.24	0.27	0.29	0.30	0.32

Note: Standard errors are clustered at the state-county-year level. Dependent variable is hourly real wage in cents in 2000 prices. The first-job is the one in which respondent worked more than two months and for more than twenty hours in a week after completing the schooling. For parents' education, being high school dropout is the control group. Other control variables are gender, race, age and parents' education. * 10%, ** 5%, ***1%. (1) HHI is the measure of ethnic diversity. Higher values of HHI mean less diversity. (2) Light-FC takes the value of one if the share of people of light-featured ethnic origins is greater than fifty-percent. The reference group is dark-featured individuals residing in dark-featured counties.

counterparts residing in light-featured counties. In other words, after controlling for the state fixed effects, the wage penalty for the dark featured individuals residing in light-featured counties disappears for all samples.

The counties classified as dark or light featured with fifty-percent threshold. To check the sensitivity of results to threshold selection, I provide estimation results from equation [2] with eighty-percent threshold.[28] Results with a higher threshold, eighty-percent, are presented in Table 3.4.C and Table 3.4.D. Results are robust for the entire sample and whites sample (columns 1 and 4). Columns 2 and 5 show that there is a wage premium for females with blonde/red hair, compared to females with brown/black hair and residing in a dark-featured county. However, the wage penalty for individuals with brown/black hair residing in the light-featured counties disappears in specifications with (Table 3.4.C) and without state fixed effects (Table 3.4.D). Thus, it can be concluded that evidence shows that there is a wage premium of having blonde/red hair in a dark-featured county. The result is stemming from whites and white females. For the white females residing in a dark-featured county leads to six-to-eight-percent wage premium. The brown/black hair females residing in a light featured area do not have such a premium.

3.4.1. Causality

In the previous section, I find that there is a wage premium for blonde females residing in dark-featured counties. This result is consistent with the hypothesis that attractive people stand out in the crowd and earn more compared to individuals without these features. However, the color feature of the county might be endogenous since it is determined by the people's selection on location to live. There might be some unobservable individual, location and ethnic

[28] Results are robust to several alternative threshold selections at the range of sixty to ninety-five percent.

Table 3.4.C
Impact of Hair Color and Color Feature of the County on Wages at the First-job
Share of Light-Featured Ethnicities>80%

Dependent Variable: Wages at the First-job	All	Female	Male	White	White Female	White Male
	1	2	3	4	5	6
Light Eyes	0.004	-0.011	0.016	-0.005	-0.031	0.014
	(0.019)	(0.024)	(0.029)	(0.021)	(0.027)	(0.033)
HHI (1)	-0.274***	-0.315***	-0.245***	-0.318***	-0.406***	-0.240*
	(0.059)	(0.088)	(0.078)	(0.096)	(0.142)	(0.124)
Light-FC (2)	-0.002	-0.006	0.001	-0.001	0.005	-0.011
	(0.039)	(0.065)	(0.043)	(0.044)	(0.072)	(0.050)
Light Hair * Light-FC	0.026	0.117	-0.077	0.018	0.099	-0.086
	(0.080)	(0.127)	(0.119)	(0.080)	(0.128)	(0.118)
Light Hair * (1-Light-FC)	0.051**	0.055*	0.046	0.053**	0.060*	0.043
	(0.024)	(0.033)	(0.036)	(0.025)	(0.034)	(0.038)
All Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
First-job Start Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,875	2,400	2,475	2,742	1,379	1,363
R-Square	0.23	0.22	0.23	0.27	0.26	0.27

Note: Standard errors are clustered at the state-county-year level. Dependent variable is hourly real wage in cents in 2000 prices. The first-job is the one in which respondent worked more than two months and for more than twenty hours in a week after completing the schooling. For parents' education, being high school dropout is the control group. Other control variables are gender, race, age and parents' education. * 10%, ** 5%, ***1%. (1) HHI is the measure of ethnic diversity. Higher values of HHI mean less diversity. (2) Light-FC takes the value of one if the share of people of light-featured ethnic origins is greater than eighty-percent. The reference group is dark-featured individuals residing in dark-featured counties.

Table 3.4.D
Impact of Hair Color and Color Feature of the County on Wages at the First-job
Share of Light-Featured Ethnicities>80%
with State Fixed Effects

Dependent Variable: Wages at the First-job						
	All	Female	Male	White	White Female	White Male
	1	2	3	4	5	6
Light Eyes	0.013	-0.000	0.020	0.009	-0.014	0.024
	(0.019)	(0.025)	(0.029)	(0.022)	(0.028)	(0.034)
HHI (1)	-0.148*	-0.051	-0.259***	-0.086	-0.047	-0.097
	(0.078)	(0.127)	(0.091)	(0.123)	(0.189)	(0.146)
Light-FC (2)	0.011	-0.008	0.042	-0.032	-0.059	0.003
	(0.049)	(0.080)	(0.058)	(0.056)	(0.090)	(0.068)
Light Hair * Light-FC	0.018	0.100	-0.114	0.012	0.090	-0.119
	(0.083)	(0.129)	(0.125)	(0.082)	(0.129)	(0.124)
Light Hair * (1-Light-FC)	0.048**	0.054	0.041	0.053**	0.058*	0.037
	(0.024)	(0.033)	(0.036)	(0.026)	(0.034)	(0.039)
All Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
First-job Start Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,875	2,400	2,475	2,742	1,379	1,339
R-Square	0.25	0.24	0.27	0.29	0.30	0.32

Note: Standard errors are clustered at the state-county-year level. Dependent variable is hourly real wage in cents in 2000 prices. The first-job is the one in which respondent worked more than two months and for more than twenty hours in a week after completing the schooling. For parents' education, being high school dropout is the control group. Other control variables are gender, race, age and parents' education. * 10%, ** 5%, ***1%. (1) HHI is the measure of ethnic diversity. Higher values of HHI mean less diversity. (2) Light-FC takes the value of one if the share of people of light-featured ethnic origins is greater than eighty-percent. The reference group is dark-featured individuals residing in dark-featured counties.

characteristics which determine selection on location to live. For example, some ethnic groups might be less likely to migrate to other places for better job opportunities. Some unobserved ethnic characteristics might affect the labor market conditions of the location. For example, one ethnic group, let's say German descents might be more productive compared to others. Then, wages would be higher for German descents in that location. The color features of German ethnic group then will affect the color feature of the region. In that case, the color feature of the county might be reflecting the productivity of the German descents, not the color feature per se. Borjas (1992 and 1995) points out that ethnic capital is an important factor affecting skills of a person and also labor market outcomes. In addition, some individuals might choose a location where people from their own ethnic group are abounded. Borjas (1992) finds evidence that people of a particular ethnic group reside among the people who are of the same ethnic background. In that case, the coefficient of the variable measuring the color feature of the county might be reflecting network effects. Thus, color feature of the county might be endogenous. The relationship between the color features of the county and the starting wages might be generated by unobservable individual, ethnic group and location characteristics.

In this section, I follow two strategies to examine whether the associations documented in the previous section are causal. First, I use the strategy introduced by Oster (2015) to investigate whether the estimates are being driven by unobserved heterogeneity across individuals and counties. Second, I use two different instruments for eye/hair composition of the counties.

3.4.2. Selection on Observables

The first strategy I employ checks the robustness of results to omitted variable bias by utilizing the method in Oster (2015). This strategy considers both the movements in the coefficient of the variable of interest and R-squared movements as control variables are included in the model. After controlling for observable factors, the estimates might still be biased due to unobserved individual and county characteristics associated with selection of county to reside.

The idea behind selection on observables is based on the assumption that the relationship between eye/hair color composition of the county and observable variables is informative about the relationship between eye/hair color composition of the county and unobservable variables.[29] In other words, bias arising from the inclusion of observed variables is informative about the bias arising from unobserved variables. How informative observables are about unobservable variables is called degree of proportionality.

Oster (2015) discusses that a set of coefficients that would yield results as if the eye/hair color composition of the county was randomized can be calculated by following the assumption of proportional selection on observed and unobserved variables. This set is called the "identified set". The rationale behind the identified set is as follows. If the coefficient of the eye/hair color composition of the county is unchanged by inclusion of individual and county control variables, one can suggest that individuals are located in different counties randomly. If that is the case, then coefficient movements (as more controls are included) should be within the bounds of the identified set, which would yield results as if the eye/hair color composition of the county was randomized. In other words, this set provides a range for the level of the stability in the non-randomized data. The identified set can be calculated by making assumptions on degree of proportionality and also on the maximum R-squared, which is obtained from the full regression with controls for eye/hair color composition of the county, observable variables and

[29] This assumption is called "proportional selection assumption".

unobservable variables. The adjusted coefficient with maximum R-squared provides the upper bound for the identified set.

The results from this strategy are presented in Table 3.5.A in Panels A and B. Panel A shows results without state fixed effects and Panel B presents the results with state fixed effects. The table shows identified sets for the assumption that observable variables are at least as important as unobservable variables, i.e. degree of proportionality equals one. Two different bounds on maximum R-Squared are employed in this study: R_{max}= 1.5$\tilde{R}$ and R_{max}= 2.2$\tilde{R}$.[30] $\tilde{R}$ is obtained from estimating equation [1] with full observable control variables and eye/hair color composition of the county. Inclusion of control variables affects the magnitude of the coefficient of color feature of the county and statistical significance change in some cases. Identified sets for all samples exclude zero regardless of the R_{max} boundary. Inclusion of coefficients moves the coefficient away from zero for almost all samples but whites and white females. In this case, I compare identified set with the 95% confidence interval obtained from the unrestricted (controlled) estimation equation. Identified set is not fully in the confidence interval, but they collapse. The results suggest that the relationship presented on Table 3.4 is causal. In the following part, I examine endogeneity by employing instrumental variable approach.

3.4.3. IV Estimates

The second strategy is to use instrumental variables to explain the role of hair color and color feature of the county on the wage-at-the-first-job after schooling. If individuals were distributed randomly across counties, then one would not expect a correlation between the color feature of the county and unobserved individual and region characteristics. However, individuals

[30] These boundaries are adopted from Oster (2015) where she obtains them in a randomized data context.

Table 3.5.A
Coefficients of 'Light-featured County' in the Baseline and Controlled Estimation Equations and Identified Sets
The Treatment Variable: Light-Featured County

	All	Female	Male	White	White Female	White Male
	1	2	3	4	5	6
Panel A: Without State Fixed Effects						
Baseline Effect	-0.012	-0.029	0.005	-0.077***	-0.073***	-0.082***
	(0.015)	(0.021)	(0.019)	(0.019)	(0.028)	(0.026)
	{0.15}	{0.15}	{0.17}	{0.19}	{0.18}	{0.21}
Controlled Effect	-0.061***	-0.061***	-0.058***	-0.072	-0.060**	-0.084***
	(0.016)	(0.023)	(0.021)	(0.019)	(0.028)	(0.026)
	{0.23}	{0.21}	{0.23}	{0.27}	{0.25}	{0.27}
Identified Set						
$\tilde{\delta} = 1, \mu = 1.5$	[-0.135, -0.061]	[-0.155, -0.061]	[-0.125, -0.058]	[-0.143, -0.072]	[-0.122, -0.060]	[-0.165, -0.084]
$\tilde{\delta} = 1, \mu = 2.2$	[-0.210, -0.061]	[-0.285, -0.061]	[-0.221, -0.058]	[-0.243, -0.072]	[-0.210, -0.060]	[-0.283, -0.084]
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: With State Fixed Effects						
Baseline Effect	-0.026	-0.001	0.052**	-0.039	-0.065*	-0.002
	(0.020)	(0.031)	(0.019)	(0.027)	(0.040)	(0.036)
	{0.17}	{0.19}	{0.17}	{0.22}	{0.22}	{0.27}
Controlled Effect	-0.009	-0.020	0.004	-0.041***	-0.067*	-0.023
	(0.021)	(0.031)	(0.021)	(0.027)	(0.040)	(0.037)
	{0.24}	{0.24}	{0.23}	{0.28}	{0.29}	{0.32}
Identified Set						
$\tilde{\delta} = 1, \mu = 1.5$	[-0.071, -0.009]	[-0.109, -0.020]	[-0.051, 0.004]	[-0.127, -0.041]	[-0.189, -0.067]	[-0.078, -0.023]
$\tilde{\delta} = 1, \mu = 2.2$	[-0.159, -0.009]	[-0.234, -0.020]	[-0.075, 0.004]	[-0.248, -0.041]	[-0.360, -0.067]	[-0.155, -0.023]
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors are in the parentheses. The coefficients reported belong to the variable "Light-Featured County" It takes the value of one if the share of individuals from light-featured ethnicities is greater than 50%, zero otherwise. * 10%, ** 5%, ***1%. 95% confidence intervals: whites [-0.114, -0.005]; white females [-0.110, -0.034].

might choose to reside in counties with specific characteristics such as crime rates, racial discrimination, labor market conditions, etc. Thus, the instrument should be correlated with the color features of the county but uncorrelated with any labor market outcomes.

First, I use state-level color features as an instrument for county color features. Changing the county of residence is easier compared to changing state of residence. Thus, individuals' decision about where to live will be more endogenous for small areas. Dustmann and Preston (2001) argue that larger area ethnic composition may not be related to individual location choices and hence be beyond the control of individuals. However, larger area composition will be highly correlated to small area ethnic compositions. Second, I use share of children (under the age of 16) of the light-featured ethnicities to reflect the color feature of the state and employ it to instrument the color feature of the county. The color feature of the state, which is determined by the share of children of the light-featured ethnicities, is going to be an instrument for the color feature of the county that is determined by the share of all individuals of the light-featured ethnic origins. Since children are not part of the labor force, the ethnic composition of population under age 16 should not have an impact on the labor market. The ethnicity information by age is obtained from 1980 census five percent sample. The ancestry information is more detailed in the individual level sample. However, it does not affect determination of the color feature of the region.

The results are presented in the Table 3.5.B and Table 3.5.C. Table 3.5.B presents results with fifty-percent threshold for the county color feature. The coefficient of the light-featured county variable is greater with both instruments (Panel A and Panel B) compared to coefficients obtained by OLS (Tables 3.4.A to 3.4.D). It implies that there is a wage penalty for dark-featured individuals residing in light-featured counties compared to dark-featured individuals residing in

Table 3.5.B
IV Estimation: Impact of Hair Color and Color Feature of the County on Wages at the First-job
Share of Light-Featured Ethnicities>50%

	All	Female	Male	White	White Female	White Male
	1	2	3	4	5	6
Panel A: *Instrument: State-level Color Feature*						
Light-FC [1]	-0.131***	-0.155***	-0.109**	-0.090**	-0.063	-0.117**
	(0.033)	(0.049)	(0.045)	(0.040)	(0.057)	(0.057)
Blonde Hair* Light-FC	0.086*	0.145**	0.027	0.066	0.105	0.025
	(0.050)	(0.068)	(0.076)	(0.051)	(0.068)	(0.077)
Blonde Hair* (1-Light-FC)	0.004	-0.036	0.046	0.029	0.013	0.038
	(0.045)	(0.067)	(0.057)	(0.048)	(0.070)	(0.061)
Observations	4,875	2,400	2,475	2,742	1,379	1,363
R-Square	0.23	0.21	0.23	0.27	0.26	0.25
Panel B: *Instrument: State-level Color Feature for 0-15 Age Group*						
Light-FC [1]	-0.143***	-0.153***	-0.137***	-0.135***	-0.096	-0.173***
	(0.037)	(0.054)	(0.050)	(0.042)	(0.061)	(0.058)
Blonde Hair* Light-FC	0.114**	0.183***	0.039	0.104**	0.152**	0.047
	(0.051)	(0.070)	(0.078)	(0.052)	(0.071)	(0.079)
Blonde Hair* (1-Light-FC)	-0.032	-0.087	0.031	-0.022	-0.051	0.011
	(0.045)	(0.063)	(0.061)	(0.048)	(0.067)	(0.066)
Observations	4,865	2,395	2,470	2,734	1,375	1,359
R-Square	0.23	0.21	0.23	0.27	0.25	0.26
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
First-job Start Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors are in parentheses. The tables report instrumental variable results. The dependent variable is hourly real wage in cents in 2000 prices. The first-job is the one in which individual worked more than two months and for more than twenty hours a week after completing the schooling. Other control variables are gender, race, age and parents' education. First stage F-Statistics are above 10 for all samples. * 10%, ** 5%, ***1%. (1) Light-FC takes the value of one if the share of people of light-featured ethnic origins is greater than fifty-percent. The reference group is dark-featured individuals residing in dark-featured counties.

Table 3.5.C
IV Estimation: Impact of Hair Color and Color Feature of the County on Wages at the First-job
Share of Light-Featured Ethnicities>75%

	All	Female	Male	White	White Female	White Male
	1	2	3	4	5	6
Panel A: *Instrument: State-level Color Feature*						
Light-FC [(1)]	0.010	0.006	0.013	0.054	0.082	0.023
	(0.064)	(0.117)	(0.073)	(0.072)	(0.119)	(0.086)
Blonde Hair* Light-FC	-0.055	0.072	-0.238	-0.073	0.011	-0.258
	(0.109)	(0.161)	(0.171)	(0.110)	(0.159)	(0.173)
Blonde Hair* (1-Light-FC)	0.067**	0.058	0.083*	0.073**	0.071*	0.084*
	(0.031)	(0.042)	(0.047)	(0.032)	(0.043)	(0.050)
Observations	4,875	2,400	2,475	2,742	1,379	1,363
R-Square	0.23	0.21	0.24	0.27	0.26	0.27
Panel B: *Instrument: State-level Color Feature for 0-15 Age Group*						
Light-FC [(1)]	0.021	0.030	0.017	0.056	0.091	0.018
	(0.070)	(0.131)	(0.079)	(0.077)	(0.129)	(0.093)
Blonde Hair* Light-FC	-0.046	0.099	-0.241	-0.058	0.044	-0.254
	(0.115)	(0.177)	(0.172)	(0.117)	(0.174)	(0.175)
Blonde Hair* (1-Light-FC)	0.062*	0.046	0.083*	0.067**	0.058	0.083*
	(0.032)	(0.044)	(0.047)	(0.033)	(0.044)	(0.050)
Observations	4,865	2,395	2,470	2,734	1,375	1,359
R-Square	0.23	0.21	0.24	0.27	0.25	0.27
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
First-job Start Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors are in parentheses. The tables report instrumental variable results. The dependent variable is hourly real wage in cents in 2000 prices. The first-job is the one in which individual worked more than two months and for more than twenty hours a week after completing the schooling. Other control variables are gender, race, age and parents' education. First stage F-Statistics are above 10 for all samples. * 10%, ** 5%, ***1%. (1) Light-FC takes the value of one if the share of people of light-featured ethnic origins is greater than seventy-five-percent. The reference group is dark-featured individuals residing in dark-featured counties.

dark-featured counties. However, when the threshold is increased to seventy-five-percent, this effect disappears (Table 3.5.C, Panels A and B).

The coefficients for the variable measuring the wage differences for blonde/red hair and brown/black hair individuals residing in dark-featured counties have mixed signs and statistically insignificant. In addition, the coefficients are lower in magnitude compared to OLS results (Table 3.5.B, Panels A and B). However, increasing the threshold to seventy-five-percent to determine the color feature of the county/state shows evidence that individuals with blonde/red hair earn more compared to their counterparts with brown/black hair residing at the same dark-featured county (Table 3.5.C, Panels A and B).

The coefficients measuring the wage differences for the individuals with blonde/red hair and brown/black hair in a light-featured county are also greater in magnitude (Table 3.5.B) with both instruments compared to OLS results presented in Tables 3.4.A through 3.4.D. Results suggest that blonde/red hair individuals earn eight-to-eighteen-percent more compared to their counterparts with brown/black hair individuals residing in the same light-featured county. However, when the threshold that determines whether the county is light or dark featured is increased to seventy-five-percent the coefficients of this variable become statistically insignificant.

3.5. CONCLUSION

As summarized in the introduction, being beautiful, tall, having white teeth and having light skin color have a positive impact on wages. The studies of Hamermesh and Biddle (1994 and 1998) show that there is a wage premium for beautiful individuals and they find some evidence that it might be due to employer/customer discrimination and occupational sorting. As

Persico at al. (2004) shows, height affect participation in club activities and Case and Paxon (2008) show that taller individuals have higher cognitive abilities, both leading to positive labor market outcomes. Taller individuals might have had better nutrition while growing up, leading to better built body. In addition, individuals with attractive features might have had preferential treatment from their teachers and peers during schooling. Combined with these, it might also be the case that individuals with good physical characteristics might develop better non-cognitive skills. It has been well documented that cognitive and non-cognitive abilities have a positive effect on earnings (see for example, Goldsmith, Veum and Darity 1997; Bowles et al. 2001; Heckman et al 2006; Goldsmith et al. 1997; Drago, 2011).

In addition to these characteristics, hair and eye color of an individual might have an impact on human capital formation and hence on labor market outcomes. Hair and eye color can be used as dimensions of exoticism. For example, if an individual has blonde/red hair and/or blue/green eyes, s/he might receive a wage premium due to having these features. However, if the individual is residing in a county where her/his hair and eye color is common, having these features- which are similar to the majority of the population- might not bring a wage premium. On the other hand, if the majority of the population has the opposite hair color, then, having these features might bring a wage premium or a wage penalty.

In this chapter, I use NLSY79 and census of population 1980 to investigate the association between eye and hair color and wages at the first-job. I focus on wages at the first-job instead of wages individuals earn in their mid-thirties- or later- to eliminate the effect of trainings, on-the-job learning, and employers' knowledge about the individual's productivity. The wage-at-the-first-job only includes returns to human capital the individual accumulated before entering the labor market not the capital s/he accumulates on the job. In addition, once the individual starts working, in time, employers might observe the individuals actual productivity. It might lead to wage adjustments. Thus, using the wage at-the-first job will not reflect employers' knowledge about the productivity but his/her expected productivity and also the employer's preference about working with attractive/beautiful people.

The natural eye and hair color of individuals is obtained from NLSY79, 1985 survey. If the individual has blue/green/hazel eyes s/he is considered as having "light-eyes" and if s/he has brown/black eyes s/he is considered as having "dark-eyes." In addition, blonde/red hair is considered as "light-hair" and brown/black hair is as "dark-hair". I find that there is approximately six-percent wage premium for blonde females and four-percent wage premium for whites. This result is consistent with the studies finding positive association between hair color and wages/earnings (Johnston, 2010; Gueguen 2012; Price, 2008). There is no evidence that hair color has an impact on wages at the first-job for males. In addition, there is no evidence that eye color affects wages.

Race is an important determinant of hair and eye color. Among non-white sample, the variation of hair and eye color is very low. Thus, in this study, I do not report the impact of hair and eye color on wages for the non-white sample. As it would be expected, there are very few non-white individuals who have light hair (blonde/red hair) and/or light eyes (blue/green eyes). In order to eliminate the impact of race on wages, I control for the race of the individual. However, to check whether the results are driven by the race differences, I estimate the regression equations only for white sample as well. The results suggest that, the main results presented in this chapter are driven by the variation of hair and eye color in the white sample and not driven by race differences.

After finding evidence that hair color has an impact on wage-at-the-first-job after schooling, I investigate whether there still is a wage premium due to having blonde/red hair (light-hair) for the individuals who reside in counties where “light-hair” or “dark-hair” is a common feature. In order to answer this question, I utilize three anthropological studies (Coon 1939; Hulse, 1963; and Geipel, 1969) to determine the predominant hair color of each ethnic group. Based on these studies, I classify each ethnic group as “light-featured” if the majority of people of that particular ethnic group have blonde/red hair and as “dark-featured” if majority of its people have brown/black hair. Then, I use this information to determine whether individuals with light-hair constitute the majority at a county by using the detailed ancestry information collected in the 1980 census of population. If the share of individuals with light-featured ethnic origins is greater than fifty-percent, I define that county as being predominantly light-featured. If it is less than fifty-percent, then, the county is predominantly dark-featured. I find that females residing in predominantly dark-featured counties earn six-percent more compared to females with brown/black hair and residing in the same county. In addition, in a light-featured county, females with blonde/red hair earn five to seven-percent more compared to females with brown/black hair. However, results are statistically insignificant.

I employed two different strategies to investigate whether the impact of having blonde/red hair on wages is causal. Whether the county is predominantly light or dark featured might be affected by the labor market conditions, ethnic and individual characteristics. In that case, the variable measuring whether the county is predominantly light or dark featured would reflect other factors that would affect both wage-at-the-first-job and also the county’s predominant hair color. To investigate this problem, first, I used the selection on observables strategy discussed in Oster (2015). This strategy examines whether the results are bias to the omitted variable bias. It considers movements in coefficients and also in R-Squared to measure the bias arising from omitting variables. Second, I employed state level color feature and share of children of the light-featured ethnicities in the state as an instrument for county's color feature. Investigation of endogeneity problem with both strategies suggests that the relationship between having blonde/red hair and wage-at-the-first-job might be causal.

In summary, having blonde/red hair has an impact on the wage at the first-job after completing schooling. Whether the county the individual resides is predominantly light or dark featured matters when analyzing the impact of hair color on wages. If a female with blonde/red hair resides in a predominantly dark-featured county, she earns a wage premium. The evidence of premium due to hair color for the wages at-the-first-job after schooling suggests that the wage premium is due to employer's perceptions not because of the productivity differences. In addition, there is some evidence of a wage penalty for the individuals with brown/black hair and residing in a predominantly light-featured county.

CHAPTER 4. THE EFFECT OF UNEMPLOYMENT INSURANCE GENEROSITY ON UNEMPLOYMENT DURATION AND LABOR MARKET TRANSITIONS: EVIDENCE FROM TURKEY

4.1. INTRODUCTION

This chapter examines the impact of unemployment insurance (UI) generosity on unemployment benefit duration, labor market transitions (transition to employment or non-participation in labor force), cheating the UI system and rejecting services of the Turkish Employment Agency. The UI benefit generosity is identified by using information on different lengths of benefit entitlement based the number of days UI premium is paid. Although there have been many studies that examine the relationship between UI generosity and unemployment duration for developed countries (the US and Europe), there are not many studies investigating this relationship for developing countries. This study contributes to the literature by examining the impact of UI generosity on unemployment duration for Turkey, a developing country.

In Turkey, the duration of unemployment has increased during the last two decades, especially short-term unemployment. The share of 1-2-months unemployment duration in total unemployment has increased from 14-percent in 1991 to 33-percent in 2012. In the same period, the share of 3-5-months unemployment duration also jumped, from 19-percent to 26-percent (Figure 4.1, Panel A). However, the share of long-term unemployment decreased slightly over the years. Since 2002 individuals who lost their jobs involuntarily are potentially eligible for the UI benefits. After the enactment of the Turkish Unemployment Insurance Law in 1999, there is a clear jump in the share of unemployed workers who lost their jobs involuntarily in total number of workers in each unemployment duration period (Figure 4.1, Panel B). For example, in 1995 there are 527 thousand workers who lost their job involuntarily and around 67-percent of them stay unemployed for almost up to a year. In 2012, the number of workers who lost their jobs

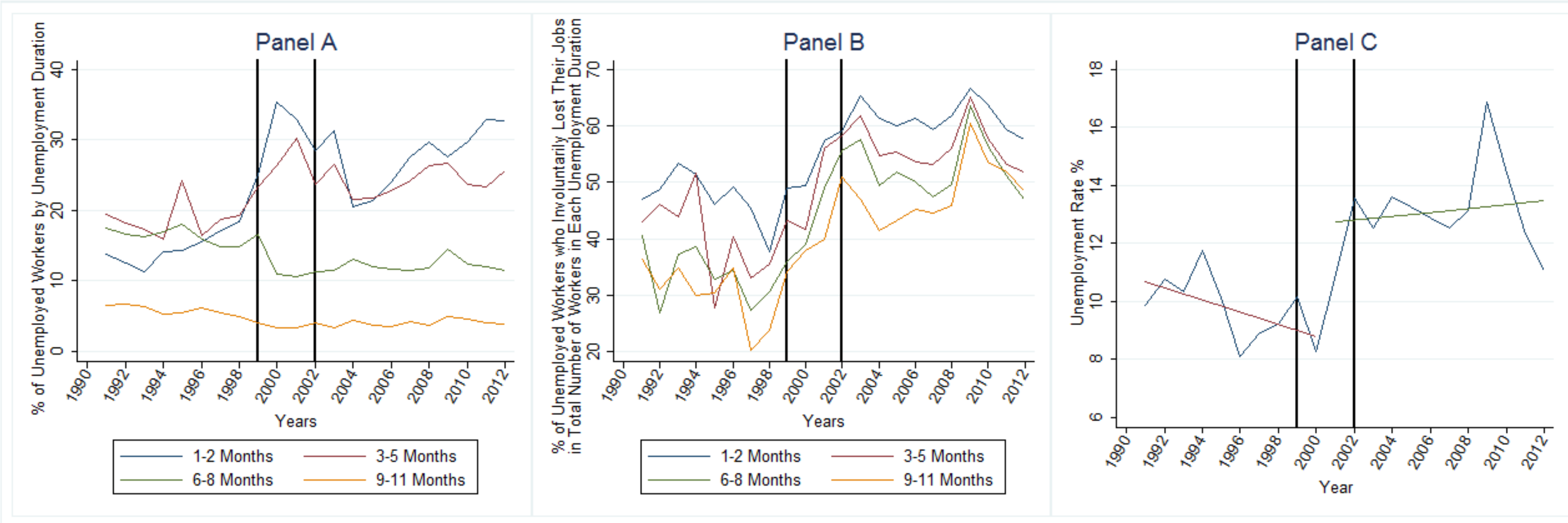

Figure 4.1
Share of Unemployed Workers by Unemployment Duration and Unemployment Rate
1991-2012

Note: TurkStat. The first reference line, 1999, represents the year "Unemployment Insurance Law" has enacted. The second reference line, 2002, shows the year the eligible workers first received UI benefit payments. Panel A: Share of Unemployment Duration in Total Unemployment by Unemployment Duration; Panel B: Share of Unemployed Workers who Involuntarily Lost Their Jobs in Total Number of Workers in Each Unemployment Duration; Panel C: Unemployment Rate.

involuntarily increases to 1,226 thousand. 81-percent of them remains unemployed for almost up to a year. Moreover, unemployment rate in Turkey has increased from around 8% in 2000 to around 13% on average afterwards (Figure 4.1, Panel C). However, it should be noted that in the beginning of the 2000s, Turkey experienced a financial crisis. It has been argued in the literature that the different unemployment rates between the US and Europe might be due to more generous UI systems in Europe (see Nickell, 1997 for discussion). Turkey has higher unemployment rates compared to both. However, some part of the increase in the unemployment duration might be attributed to the UI. Thus, from a policy maker's standpoint, it is important to understand the role of UI benefits on unemployment duration.

According to the basic job search theory, an increase in the unemployment compensation leads to longer unemployment periods because of the increase in reservation wages and decrease in the cost of unemployment.[31] The existing literature shows that unemployment insurance generosity, in the form of benefit amounts and/or benefit durations, has a positive impact on the unemployment duration and negative effect on transition to employment from unemployment. The association between UI generosity and unemployment duration is mostly investigated for the US and Europe.

In the US, since the Extended Unemployment Compensation Act in 1971, studies investigating the impact of extended UI benefits on unemployment duration find that longer benefit duration leads to longer unemployment spells. There is an extensive literature on the

[31] For instance, UI benefits might help unemployed workers to maintain their consumption and savings while searching for a job. Browning and Crossley (2001) find a small and marginally significant impact of a decrease in unemployment benefit on total expenditures. Gruber (1997) finds that in the absence of UI, the consumption would have fallen by twenty-two percent and it decreases by seven percent in the presence of the program. It suggests evidence that UI helps workers to smooth their consumption.

topic. Thus, I will summarize the ones that are most closely related to this study.[32] For example, Ehrenberg and Oaxaca (1976) find that 1-percent increase in the UI benefit replacement rate lead to 0.2-0.5 weeks longer unemployment duration for young males and females, respectively. In addition, they show that more generous unemployment benefits decrease the duration out of labor force. Moffitt (1985) uses both UI benefit amount and the change in benefit duration as generosity measures and finds that a 10-percent increase in benefit amount increases unemployment duration by a half week while one additional week of UI benefits leads to 0.15 weeks longer unemployment duration. By analyzing benefit recipients and non-recipients Katz and Meyer (1990) shows a similar impact of longer UI benefits on unemployment duration. [33] Gritz and MaCurdy (1997), find that one-week increase in the weeks of eligibility increases the unemployment duration about 0.1 week. Moffitt and Nicholson (1982) also find the same impact of UI generosity on unemployment duration.

Card and Levine (2000) investigate the impact of extended benefits in New Jersey in 1996 on unemployment benefit recipiency and duration. Contrary to existing evidence in the US, they find that extended benefits have no impact on the average unemployment duration. However, they show that the percentage of unemployed people exhausting their benefits increase modestly, by 1.5-percentage points. They also simulate the long-run effect of the benefit extension and suggest that one additional week of benefits would lead to 0.08 week increase in the number of weeks unemployed workers collect UI benefits. This evidence is similar to what the studies above find.

[32] For a detailed review of studies prior to 1991, see Atkinson and Micklewright (1991).

[33] The results in the paper show that one-week increase in UI benefit duration increases unemployment duration by 0.16-0.20 weeks.

In a more recent study, Schwartz (2013) investigates the impact of 1991 Stand-by Extended Benefit Program (SEB) in the US. Different from the previous studies proving evidence from the US, he employs regression discontinuity design. The results show that one additional week of benefits lead to 0.06-0.13 weeks longer unemployment duration. This evidence is very similar to what previous studies find. Farber and Valletta (2013) use the extended benefits in the US in the 2000s and find that extended benefits has no effect on the probability of finding a job. However, they show that extended benefits lead to 7-percent higher expected unemployment duration during the Great Recession. In addition, benefit extensions decrease the probability of entering out of labor force.

Studies from Europe mainly use the difference in length of UI benefit entitlement based on some eligibility criteria (e.g. age, region) to investigate the impact of UI generosity on unemployment duration and labor market transitions. For example, Hunt (1995) utilizes the law changes in the West Germany during 1980s to analyze the impact of UI generosity on unemployment duration. Due to changes in the law, the level of UI compensation and its duration changes for workers without children and workers aged over 41, respectively. Hunt (1995) finds evidence that longer UI benefit periods lead to longer unemployment durations for older workers compared to younger workers. In addition, she shows that longer benefit durations decrease the probability of transitions to employment and out of the labor force. In a study that makes use of regression discontinuity design, Caliendo, Tatsiramos and Uhlendorff (2013) find similar results for Germany. Germany increased the duration of UI benefits from 12 months to 18 months at the age of 45 during 2000s. They show evidence that probability of finding a job decreases by 23% (men) and 24% (women) by additional 6 months of benefit period.

Due to the availability of the detailed administrative data, there are several studies investigating the impact of UI generosity on unemployment duration for Austria. During the period 1988-to-1993, elderly workers in some regions across Austria received unemployment benefits for additional 179-weeks. Lalive and Zweimuller (2004) implement a difference-in-difference-in-difference approach to investigate the impact of 179-week increase in the duration of unemployment benefits on unemployment duration. They find that an additional week of benefits increases the unemployment duration by 0.06 weeks and 179-week increase in benefit duration decreases transition to employment by 17%. Lalive (2008) investigates the impact of the same policy change on unemployment duration with a different identification strategy. They employ regression discontinuity design to identify the impact of UI generosity for men and women. They find that one additional week of UI benefit increases the unemployment duration of men by 0.09 weeks and of women by 0.32 weeks. In addition to these studies, Card, Chetty and Weber (2007) investigate the impact of benefit generosity on unemployment duration in Austria with an alternative structure of the Austrian UI Law. They use the differences in entitled benefit durations based number of months a worker was employed in the past 5 years to measure the generosity of UI. In Austria, workers with 36-month employment in the past 5 years receive 20 weeks benefits while workers who have more than 36 months receive 10 extra weeks. They show that this additional 10-week UI benefits leads to 5-9% decrease in probability of finding a job.

In addition to its impact on unemployment duration, more generous UI benefit might increase the overall unemployment rates. The longer unemployment spells might lead to higher unemployment rates. Using variation in UI system across states, Moomaw (1998) finds that more generous UI systems are associated with higher unemployment rates. Schwartz (2013) utilizes

Stand-by Extended Benefit implemented in the US in 1991 and finds that extended benefit duration increases county unemployment rates by 14% in the states adopting the program. Farber and Valletta (2013) find that extended benefits during the Great Recession increased the unemployment rate by 0.4-percentage points, which is lower than what Schwartz (2013) finds.

As most of the existing studies, in this chapter, I examine the impact of UI generosity on unemployment duration and labor market transitions through changes in the duration of UI benefits. According to Turkish Unemployment Insurance Law, which is enacted in 1999, number of days a worker is entitled to UI benefits is a gradual function of the number of days the worker has paid UI premium in the last three years prior to losing her job. Workers with less than 900-paid-premium-days in the last three years receive 6-months of UI benefits, while those who have 900-paid-premium-days or more receive 8-months of UI benefits. The two-month difference in UI benefit qualification is considered as "extended benefits." In Turkish UI system, after the benefits are exhausted there is no additional assistance provided to unemployed individuals.

I employ a unique data set obtained from Turkish Employment Agency (ISKUR). The data set includes administrative records of all unemployed workers who are registered to the UI system, lost their jobs involuntarily between 2002 and 2012 and filed a claim to ISKUR for UI benefits. The data contain information on benefit taker characteristics such as age, gender, marital status, education levels, and the region of residence. In addition, information on the date benefit taker lost her job, why the job has ended, industry the she was working in, how many days of UI premium she has paid within three years prior to losing her job and the number of days she utilized UI benefits is available in the data. More importantly, data contains information that is not included in the data sets that are employed in the existing literature: whether UI benefits were stopped and if so what was the reason they were stopped and the amount of UI benefits collected by the benefit taker. The detailed information on the reasons UI benefits are stopped allow me to measure different labor market states.

Most of the studies summarized above make use of difference-in-difference approach. In this chapter, I employ regression discontinuity approach as the identification strategy. The empirical analysis uses the discontinuity in the benefit duration set by the UI Law to identify the causal effect of UI generosity on unemployment duration, labor market transitions, cheating the UI system and rejecting the services of the Agency. In other words, the identification comes from the sharp discontinuity in the maximum duration of UI benefit that workers are entitled to. The workers with less than 900 premium days are entitled to 6-month benefits while benefit takers who have paid more than 900 premium days are entitled to 8-month benefit periods. The former group is the control group and the latter is the treatment group. I utilize local linear regressions with a bandwidth of 60-paid-premium-days as the main estimation specification.

The main identification assumption is that receiving longer UI benefits is determined only by the number of days a worker has paid UI premiums and not by her characteristics. In addition, the worker has no control over the threshold since the UI Law sets it. In order to check potential selection issues that might invalidate the identification strategy, I show two validation tests. First, I investigate whether the benefit takers can fully manipulate assignment to longer UI benefit periods. In other words, the running variable (paid-premium days) should be continuous at the cutoff. Second, I check whether predetermined benefit taker characteristics are balanced around the cutoff. It is important to capture the impact of UI generosity on unemployment duration but not the impact of some different benefit taker characteristics on the duration. Both exercises provide results suggesting that the regression discontinuity design is valid.

I find that extended benefits increase the unemployment duration by forty-one-days. In other words, one additional week of UI benefits lead to 0.7 weeks of unemployment duration. This is threefold of what existing literature finds for the developed countries. More generous benefits decrease the probability of transition to employment. The impact on the transition to employment is similar to the results of those studies. However, I find that extended benefits lead to higher probabilities of transition to non-participation in labor force. A few studies investigating transition to out of labor force find that more generous UI benefits lead to lower probabilities of entering out of labor force (for example van den Berg, 1990; Carling, Edin, Harkman and Holmlund, 1996; and Farber and Valletta, 2013). Different than the existing studies, the data allows me to investigate the impact of UI generosity on the probability of cheating the UI system, which is an illegal way of receiving UI benefits while working on a wage-earning job. I find that extended benefits decrease the probability of cheating by four-percentage points. In addition, the Agency provides additional services such as job placement services and vocational development trainings. The penalty of refusing a job offer arranged by the Agency unjustifiably or not attending to trainings after agreeing to receive them is losing UI benefits. I find that extended benefits decrease the probability of rejecting the Agency's services by two-percentage points.

Moreover, I investigate whether the impact of generosity on outcomes is different for females and males and also for married and single benefit takers. The female labor market decisions are different than those of males. Extended benefits, on average, lead to ten-days longer unemployment duration for females. In addition, transition to non-participation in the labor force is more likely for females compared to males. Probability of cheating the system and rejecting services is lower for male benefit takers who are entitled to extended UI benefits compared to their female counterparts. Furthermore, extended benefits increase the unemployment duration for almost additional three-days for married benefit takers compared to singles. In addition, the magnitude of the impact of UI benefit generosity on transition to employment is smaller for singles. These results suggest that married benefit takers utilize the UI benefits for longer periods compared to single benefit takers. They might be enjoying the UI benefits longer due to spousal support (both financial and emotional). For single benefit takers, extended benefits lead to lower probabilities of transition to non-participation in the labor force. However, for those who are married, it increases the probability of entering non-participation.

In order to check the robustness of the results, I estimate the main specification equation with different bandwidth selections and polynomial degrees. First, I show that results are robust to alternative bandwidth selections. The coefficient estimates with the optimal bandwidths obtained by the approaches introduced by Calonico, Cattaneo and Titiunik (2014) and Imbens and Kalyanaraman (2012) yield the same results. In addition to optimal bandwidth selections, I show the coefficient estimates from alternative bandwidths of 30 and 90-paid-premium-days. In the main specification, it is assumed that the functional form is linear. In order to test the sensitivity of results to this assumption, I estimated the coefficient of UI benefit generosity with alternative specifications and with the parametric approach. The results from these alternative specifications suggest that results are robust to different model specifications. In addition, including benefit taker characteristics does not alter the magnitude or sign of the estimated coefficients.

The rest of the chapter is as follows. Section 2 introduces the unemployment insurance system in Turkey and provides details on the UI benefit eligibility. Section 3 is the empirical strategy and section 4 is the data and descriptive statistics. Section 5 presents the estimation results and section 6 is the robustness checks. Last, section 7 concludes.

4.2. UNEMPLOYMENT INSURANCE SYSTEM AND BENEFIT ELIGIBILITY IN TURKEY

In Turkey, Unemployment Insurance Law is enacted in 1999 and put into effect in June 2000. Workers made the first UI premiums payments in 2000 and eligible workers received the first UI benefit payments in March 2002. Since the date the law has been put into effect, workers have to register to the social security system, and employers have to provide it to all their workers.

The UI benefits are collected under Unemployment Insurance Fund. All payments and services are financed through these funds. The main source of UI funds is the UI premium. Workers pay 1% of their gross earnings as UI premium, employer contributes by paying 2% and government pays 1% of it. The Social Security Institution handles the collection of UI premiums and their transfer to the Unemployment Insurance Fund. It also is responsible for keeping the records while Turkish Employment Agency (ISKUR) is charged for all other services and procedures. The services provided by the Agency are defined in the UI law as the payment of general health insurance premiums, distribution of UI compensation, providing job placement services and provision of vocational development and training courses. The Agency uses funds from the Unemployment Insurance Fund to make UI payments and provide all other services to the benefit takers.

After losing the job, the worker has to apply to the Agency within 30-days to receive UI benefits. In a typical case, UI applications are finalized in the month the claim is filed. The first eligibility criterion for the UI is that the worker should be registered to the social security system and the Turkish Employment Agency. Second, the worker should lose her job involuntarily, i.e. out of her will, intent or fault. Plant closure, privatization, end of a temporary job, and termination of the employment-contract by the employer or the employee under certain conditions (and defined by several different articles of the labor law) are covered under the definition of "involuntary job loss". Third, the worker should have paid unemployment insurance premium for at least 600 days within the last three years immediately preceding the job loss. She also should have paid UI premium continuously within the last 120 days (immediately preceding the job loss) before the termination of the employment-contract. If the worker meets these criteria, she becomes eligible for unemployment insurance benefits for a certain period of time.

The length of the unemployment insurance benefit depends on the number of days the worker pays the UI premiums. The Article 50 of UI Law states that if the worker has paid premiums for at least 600 days, she becomes eligible for 180 days (6-month) of UI benefit period. If the worker has paid UI premium for at least 900 or 1080 days, then the worker is eligible for 240 or 300 days (8-month or 10-month) of UI benefits, respectively. Figure 4.2 shows the number of paid UI premium days and qualified days for UI benefits.

Benefit takers receive the first UI benefit payment by the end of the month following the date they are entitled to UI benefits. Along with the UI benefit payments, benefit takers also receive other services that are intended to help benefit takers to leave unemployment for employment. These services include job placement services and providing training courses and vocational development courses. In addition, benefit takers and their families are covered by the general health insurance during UI benefit recipiency.

The amount of UI benefit payment depends on the benefit taker's gross earnings in the last four months (120 days) at the previous job. The UI payment amount is calculated as 40-

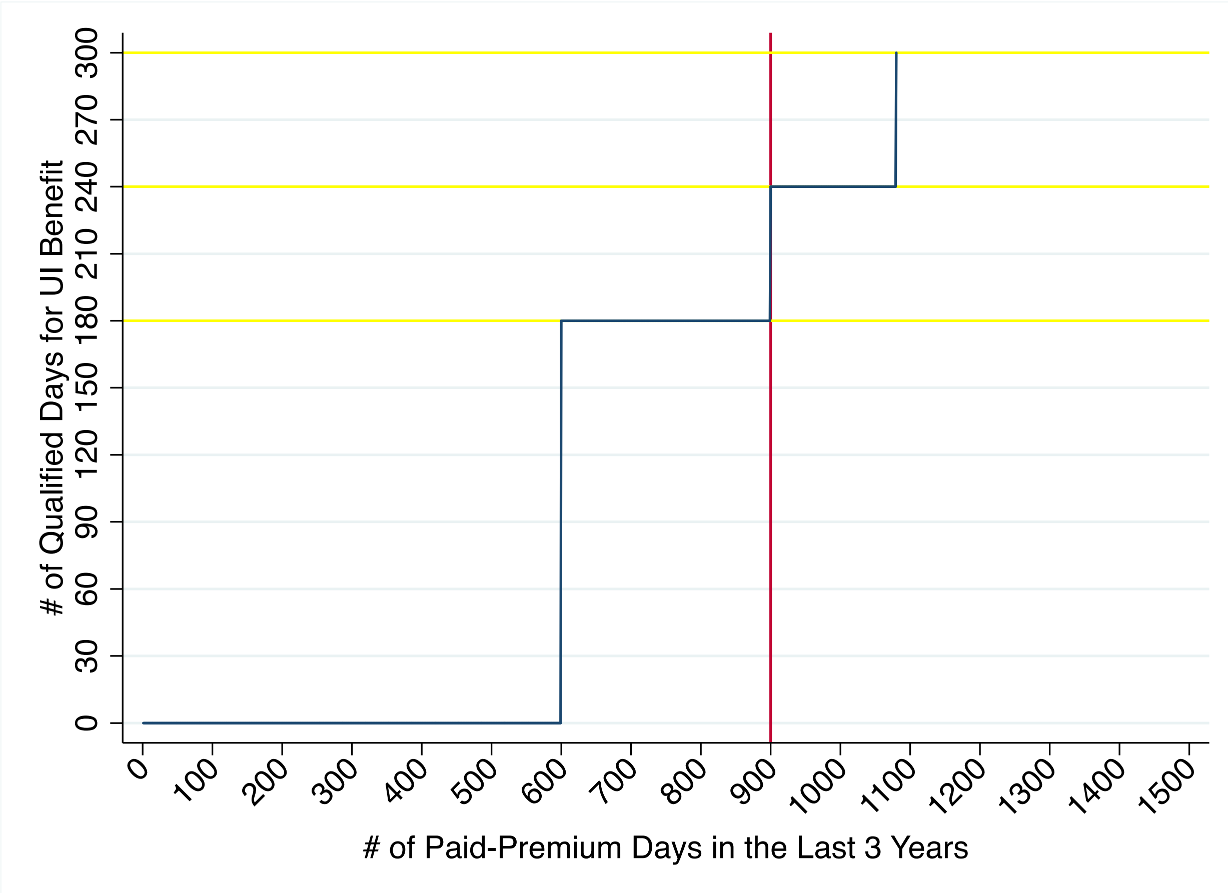

Figure 4.2
Number of UI Premium Days and Qualified Days for UI Benefit

Note: The Article 50 of Unemployment Insurance Law determines the number of days a worker receives Unemployment Insurance Benefit. According to the article, an insured unemployed worker who has paid unemployment insurance premiums for at least 600 days is entitled to receive UI benefits for 180 days. If the worker has paid unemployment insurance premiums for at least 900 days, she is entitled to receive UI benefits for 240 days. If she worked and paid unemployment insurance premiums for 1080 days, she is qualified to receive UI benefits for 300 days.

percent of daily average "gross" earnings. The upper limit is eighty-percent of the "gross" monthly minimum wage set for the employees older than sixteen years of age. UI payments are not subject to taxation or any other cuts.[34]

[34] There is a one-time 0.006% stamp tax collected on the UI benefit payments. However, the amount is negligible.

The continuation of UI benefit recipiency within the entitled period depends on some conditions that benefit takers have to comply. Benefit takers do have to inform the Agency when they find a new wage-earning job within 15 days following the recruitment. If a benefit taker works illegally without registering to the UI system or fails to report the new job to the Agency, UI payment will be stopped. Additionally, the benefit taker will have to pay back the UI payment received since the start date of the new job along with the legal interest rate. The same sanction is applied if the worker fails to report recipiency of retirement pension. Moreover, if the benefit takers reject a job that the Agency finds (and is similar to the benefit taker's previous job in terms of wages, working conditions and is in the area where the benefit taker resides) without any reasonable explanation, UI payments will be stopped. In addition, if the benefit taker rejects the vocational trainings or does not attend to trainings after accepting them, the Agency suspends UI payments. In this particular case, if the benefit taker changes her attitude, the Agency might restart the payments. However, the benefit taker will not be able to receive UI payments for the days she has lost.

4.3. EMPIRICAL STRATEGY

This section explains the empirical strategy and identification of the impact of UI generosity. In addition, I provide evidence on the validity of the identification strategy.

4.3.1. Identification

I utilize a sharp regression discontinuity design to estimate the causal effect of UI generosity on unemployment duration, transition to employment or non-participation, cheating and rejecting services. The discontinuity arises from the number of days UI premium is paid in the last three years immediately preceding the job loss. Individuals who pay UI premium for less than 900 days are entitled to 6-month UI benefit period while individuals who pay more than 900 days are entitled to 8-month UI benefit period. Assignment to more generous UI benefits (extended benefits) is measured as:

$$Entitled\ Benefit\ Duration = \begin{cases} 1, & if\ PD \geq 900 \\ 0, & if\ PD < 900 \end{cases}$$

PD is the number of paid-premium-days and 900-paid-premium-days is the cutoff. In the sharp regression discontinuity design, the causal impact of UI benefit generosity on outcome variables is identified at 900-paid-premium-days cutoff.

To estimate the causal effect of UI generosity, I follow Hahn, Todd and van der Klaauw (2001) and employ local linear regression.[35] The estimation equation is of the form:

$$O_i = \alpha_0 + \alpha_1 EBD_i + \alpha_2(PD_i - PD_0) + \alpha_3 EBD_i(PD_i - PD_0) + \varepsilon_i \qquad \textbf{[1]}$$

The data have sufficiently large observations to proceed with non-parametric approach. In addition, this specification allows different functional forms on both sides of the cutoff, PD_0 =900 premium days. PD_i is the number of days the benefit taker has paid UI premium within three years immediately preceding her job loss. O_i is the outcome variable. The outcome variables are unemployment duration, transition to employment, transition to non-participation in

[35] Hahn, Todd and van der Klaauw (2001) show that local linear estimator has advantages over standard kernel estimators and suggest that local linear estimator is a better choice than kernel estimators. However, employing kernel estimators provides similar results to the ones presented in the next section. This evidence can be interpreted as support to robustness of results obtained by local linear regressions.

labor force, cheating the UI system and rejecting services from the Turkish Employment Agency. The variable EBD_i is the variable of interest measuring the UI benefit generosity. It is an indicator variable taking the value of one if the worker is entitled to 8-month ($PD_i \geq 900$) UI benefit period, and zero if she is entitled to 6-month ($PD_i < 900$) UI benefit period. The coefficient α_1 measures the average causal effect of UI generosity on outcomes at the 900-paid-premium-day threshold, PD_0. This is a sharp regression discontinuity design; hence it identifies the local average treatment effect. α_2 and α_3 measure the direct effects of the forcing variable on average outcome variable.

For the local linear regression, the choice of optimal bandwidth is important. Across the outcome variables, the optimal bandwidths generated by Calonico, Cattaneo and Titiunik (2014) and Imbens and Kalyanaraman (2012) (CCT and IK hereafter) procedures fall between 40 to 71 paid-premium days. For simplicity and to have the same sample across these outcomes, I chose 60 paid-premium days as the default bandwidth. Table C.1 shows the optimal bandwidths obtained by CCT and IK methods. The next part discusses the validity of regression discontinuity design.

4.3.2. Validity of RDD

The quasi-random nature of the RD design bases on the assumption that individuals cannot manipulate the assignment variable, which is the eligibility to longer UI benefit periods. The assignment to treatment around the cutoff should be random. If this assumption does not hold, then RD design is no longer valid. Some workers might try to alter the timing of the job loss (e.g. layoff) by making a deal with the employer. For example, consider a worker who has 890 paid-premium-days and being laid off today. She might ask her employer to keep lay-off on hold for ten more days so that she can be eligible for 8-month UI benefit period instead of 6-month period. However, during this extension, employer has to pay the worker's wage.[36] In addition, the worker has to be registered to the social security system during this extension. It means that not paying or paying a lower wage is not an option for the employer. Hence, keeping the worker for ten more days becomes costly. Thus, employer might choose not to give the extension to the worker.

Figure 4.3 shows the distribution of paid-premium-days within the last three years immediately preceding the job loss relative to the 900-paid-premium-days cutoff. The density looks smooth at the cutoff suggesting that there is no manipulation of the assignment variable. It is worth noting that, actually there is a jump at the density at 0 (900 paid-premium days) cutoff. However, it is not unique. It happens on every thirty-day period or at the end of each one-month period. It is possible that these jumps are actually driven by the fact that employers let workers go at the end of the month that is generally the end of the contract-term. In general, contracts start on the 1st of the month and end at the end of the month (on the 30th). The estimated discontinuity at the cutoff is statistically insignificant. This leads to the conclusion that the distribution of benefit takers around the cutoff is continuous and there is no significant manipulation of the assignment variable. The results are robust to different bandwidth selections. Estimated discontinuities for different bandwidth selections are presented in Table C.2.

Another way of testing the validity of the RDD is to check whether pre-determined benefit taker characteristics are locally balanced on each side of the cutoff point (Lee and Lemieux, 2010). If a discontinuity was not observed at the cutoff point, it would indicate that assignment is a local random event. If workers who just miss the cutoff point are identical to the

[36] This wage includes employer's contribution to UI fund for the worker. The employer is contributing to the UI by paying 2% of worker's earnings as UI premium.

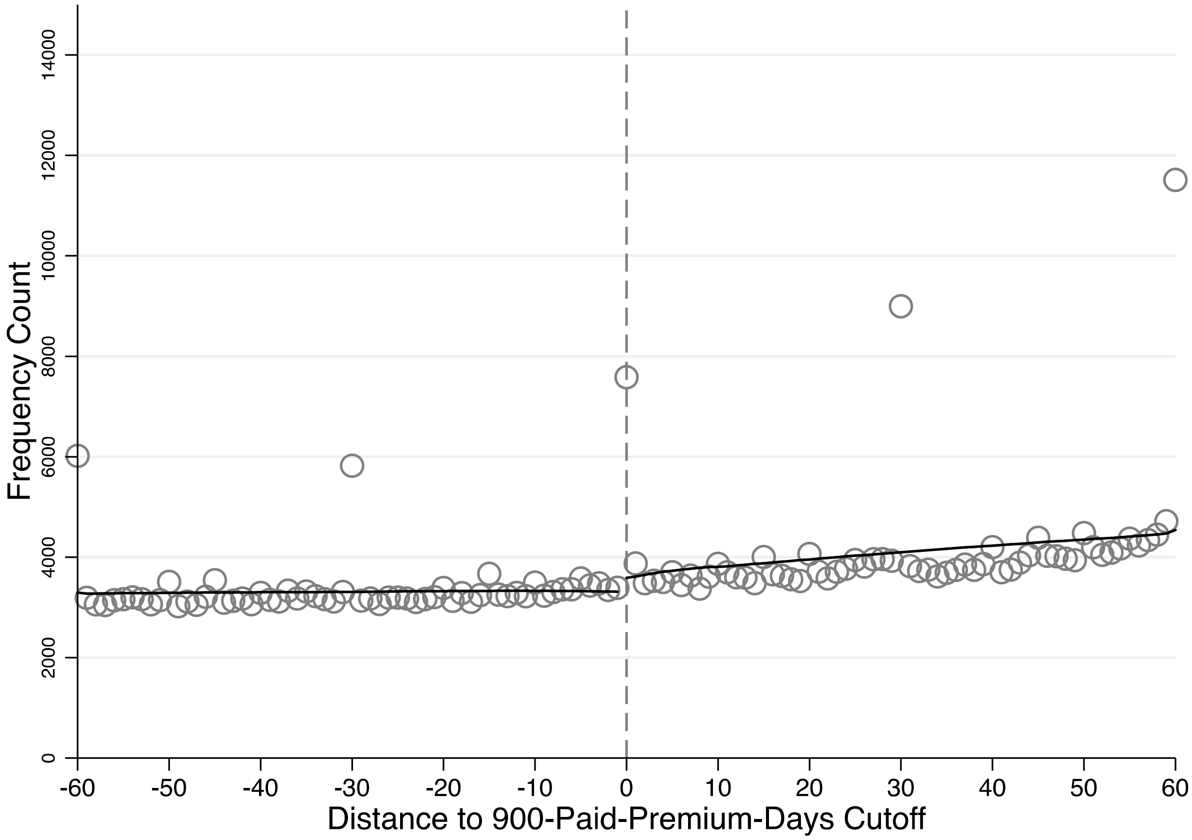

Figure 4.3
Distribution of UI Premium Days Relative to the 900-Premium-Days Cutoff

Note: Each circle indicates the number of unemployed individuals with a distance from their cutoff. Using each of these cells as an observation, the curve is predicted from Local Linear Regressions with a bandwidth of 60 days. The estimated control mean is 3,590 and the estimated discontinuity is -280.16 with p-value=0.449. The cutoff is normalized so that the zero represents 900 paid-premium-days.

workers who just make it, except that they are entitled to longer UI benefit periods, then difference in the mean outcomes can be attributed to the treatment. The available predetermined worker characteristics in the data are UI payment amount, gender, marital status and education. Table 4.1 presents coefficient estimates from the main regression specifications in which predetermined variables serve as dependent variables. I show that number premium days and these variables are not associated (columns 1 to 4).

Table 4.1
Balance Around the Cutoff

	Gender (Female)	Married	High School Graduate	Daily UI Benefit Amount	Predicted Unemployment Duration
	(1)	(2)	(3)	(4)	(5)
PD>900	-0.005	0.011	-0.003	0.028	-0.007
	(0.005)	(0.007)	(0.003)	(0.063)	(0.157)
Observations	450,225	450,225	450,225	450,225	450,225
$PD_0 - 60$	198,770	198,770	198,770	198,770	198,770
$PD_0 + 60$	251,455	251,455	251,455	251,455	251,455

Note: Estimated standard errors, clustered on year and premium days, are displayed in parentheses. Each coefficient on UI benefit generosity is estimated with local linear regression with a bandwidth of 60 days. The coefficients show the effect of being entitled to longer UI benefit periods on predetermined characteristics. * 10%, ** 5%, ***1%.

In addition, to test whether predetermined variables are jointly discontinuous, I obtain the predicted values of the outcome variables by regressing each of them on a complete set of benefit taker characteristics. In Table 4.1 column (5), I show the result only for the main outcome, unemployment duration. It suggests that there is no discontinuity in the predicted unemployment duration.[37] The results presented in Table 4.1 are robust to different bandwidth selections.[38] Figure 4.4 shows the discontinuity at the threshold for predetermined benefit taker characteristics.[39] Tests provided in this section suggest that regression discontinuity design is valid.

[37] The results where joint discontinuity is tested using other dependent variables also support this evidence. The results are available upon request.
[38] The results from the local linear regressions with optimal bandwidths chosen by IK and CCT are presented in Table C.3.
[39] Figures for the predicted outcome variables are presented in Figure C.1 in Appendix C.

4.4. DATA AND DESCRIPTIVE STATISTICS

4.4.1. Data

I use an administrative data obtained from Turkish Employment Agency (ISKUR). The data include information on individuals who are unemployed, are in the social security system, lost their jobs involuntarily, and initiated a claim for UI benefits during the period 2002-2012. The registration to social security system is mandatory for all workers in Turkey. However, it is voluntary to register at the agency and file a claim for UI benefits.[40] The observation period for each benefit taker starts with the recipiency of UI benefits and lasts until the UI benefits are stopped. The data include information on the reason UI benefits are stopped. Using this information creates the outcome variables. Exhaustion of UI benefit duration, finding a new job, working in a wage-earning job while receiving UI benefits, being eligible to retirement/retirement payments, military service, rejecting training services, rejecting jobs suggested by the Agency and death are among these reasons. Due to any of these reasons (except death), if the worker is no longer receiving UI benefits, it is assumed that unemployment benefit period has ended. Hence, the benefit taker transits from unemployment to employment or non-participation in the labor force, or remains in unemployment. During the time the benefit taker receives the UI benefits, he is assumed to be unemployed. The length of UI benefit recipiency is the main outcome variable and it shows the duration of unemployment which is measured in days.

The two main reasons of leaving unemployment are examined in the study. The first is the transition from unemployment to employment. It is an indicator variable taking value of one if the benefit taker finds a job within the first six-month period following her job loss. It takes the

[40] In 2012, there are over 2 million unemployed individuals registered to the agency. Twenty six percent of them initiated a claim for the UI benefits.

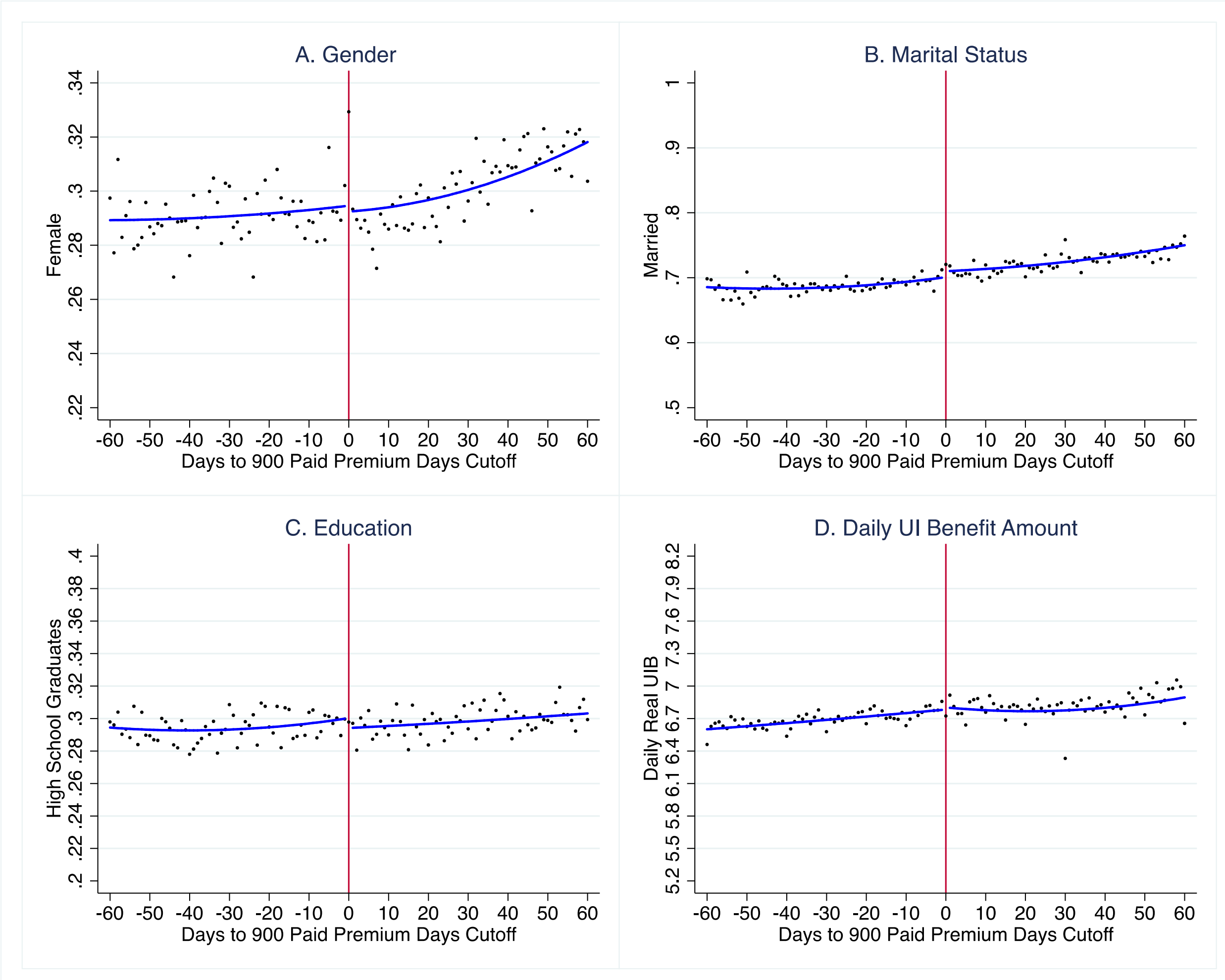

Figure 4.4
The Effect of Unemployment Insurance Benefit Generosity on Pre-Determined Benefit Taker Characteristics

Note: Each panel shows the unconditional means for pre-determined variables by each value of the running variable, paid-premium-days. Solid lines are fitted values of pre-determined characteristic from a local linear regression with a bandwidth of 60 days. If the benefit taker's premium days are less than 900-days s/he is entitled to 6-month UI benefit period. If her/his premium days are greater than 900-days, the benefit taker is entitled to 8-month benefit period. The cutoff is normalized so that the zero represents 900 paid-premium-days.

value of zero if she is unemployed in the first six-month period. The second is the transition to non-participation in labor force and shows whether the benefit taker leaves labor force in the first six-month period. It takes the value of one if s/he retires, joins to military for the mandatory service, is not ready for work or temporarily unable to work. In other words, it takes the value of one if the benefit taker is not in the labor force. It takes the value of zero if the benefit taker transits to employment or remains in the unemployment.

One other outcome of interest is whether the benefit taker cheats the system. According to the UI Law, the benefit taker has to report the new job to the agency within 15 days following the recruitment. If benefit taker fails/chooses to do so, she receives a wage from the new job and also the UI benefit, which is illegal. The variable measuring the probability of cheating the system takes the value of one if UI benefits are stopped because the benefit taker was caught working in a wage-earning job while receiving UI benefits. The variable takes the value of zero if the benefit taker reports the new job (transits to employment legally) or remains unemployed. Along with the UI payments, the Agency provides additional services (trainings and job placement) to help benefit takers move from unemployment to employment. If the benefit taker rejects trainings or suggested jobs, the UI benefits are stopped. The variable measuring the probability of rejecting services takes the value of one if the UI benefit is stopped due to these reasons. It takes the value of zero, if the benefit taker transits to employment or remains unemployed. Detailed definitions of the variables are provided in Table C.4.

Benefit takers' demographic characteristics, education, and the industry s/he was working in are available in the data. The unemployed workers who initiated a claim for UI benefits but were not eligible for UI benefits are excluded from the data since there is no information on their unemployment duration or labor market transitions. In addition, benefit takers who have missing information on demographic characteristics, unemployment duration and reason they left their jobs are dropped from the sample. The analyses focus on benefit takers who had at least 20-months of labor market attachment at the time of their job loss. The final sample consists of around 1.8 million benefit takers who are at the ages of 16 to 65 and are entitled to 6-months or 8-months UI benefit between years 2002-2012.

4.4.2. Descriptive Statistics and Graphical Evidence

Descriptive statistics are presented in Table 4.2. As it is mentioned above, workers who paid UI premium for less than 900 days are eligible for 6-months of UI benefits and workers who paid more than 900 days (and less than 1080 days) are eligible for 8-months of UI benefits. The control group consists of benefit takers who are entitled to 6-month and treated group covers benefit takers who are entitled to 8-month UI benefit period. On average, benefit takers in the control group had paid 811 days UI premium and benefit takers in the treated group had paid 1,016 days. The number of paid-premium days is 116 days more than the 900 paid-premium days threshold for the treated and it is 89 days less than the threshold for the control group.

The unemployment duration is on average 5.8 months. It is lower, around 5 months, for the benefit takers in the control group and it is around 6 months for the benefit takers in the treated group. As expected, the average unemployment duration is higher and probability of transition to employment is five-percentage point lower for the benefit takers who are entitled to more generous benefits. However, probability of transition to non-participation in labor force is one-percentage point higher. Probability of cheating the system and probability of rejecting the services provided by the Agency are higher for the control group. The opportunity cost of cheating or rejecting help is higher for the treated group.

Figure 4.5 presents graphical evidence of the impact of unemployment insurance generosity on outcome variables. In all figures, the forcing variable (paid-premium-days) is normalized so that 900th day, the cut-off, is time zero. The fitted values from linear regressions

Table 4.2
Descriptive Statistics

Variable	All Mean (Std.Dev.)	Non-Treated Mean (Std.Dev.)	Treated Mean (Std.Dev.)
Unemployment Duration	176.08	151.61	187.80
	(68.95)	(48.12)	(74.14)
Transition to Employment	0.416	0.449	0.397
	(0.493)	(0.497)	(0.489)
Transition to Non-Participation in Labor Force	0.022	0.016	0.031
	(0.146)	(0.125)	(0.172)
Cheating the System	0.077	0.111	0.063
	(0.266)	(0.314)	(0.243)
Rejecting Agency's Services	0.016	0.030	0.010
	(0.124)	(0.170)	(0.100)
Number of Paid-Premium Days	949.37	810.69	1015.76
	(109.65)	(51.64)	(53.74)
Entitled	220.58	180	240
	(28.07)	-	-
The Daily UIB	7.155	6.617	7.413
	(4.456)	(6.362)	(3.106)
The Sum of UIB	1,264	1,000	1,390
	(970)	(1,173)	(827)
Reason UIB Ended/Cut			
Reason 1	0.002	0.002	0.003
	(0.051)	(0.049)	(0.052)
Reason 2	0.012	0.012	0.013
	(0.111)	(0.110)	(0.112)
Reason 3	0.001	0.002	0.002
	(0.043)	(0.040)	(0.044)
Reason 4	0.009	0.003	0.010
	(0.088)	(0.058)	(0.988)
Reason 5	0.000	0.000	0.000
	(0.013)	(0.004)	(0.016)
Reason 6	0.069	0.067	0.070
	(0.254)	(0.250)	(0.256)
Reason 7	0.001	0.001	0.001
	(0.031)	(0.031)	(0.031)
Reason 8	0.001	0.001	0.001
	(0.027)	(0.025)	(0.028)
Reason 9	0.402	0.369	0.418
	(0.490)	(0.482)	(0.493)
Reason 10	0.000	0.000	0.000
	(0.015)	(0.013)	(0.016)

(Table 4.2 Continued)

Reason 11	0.000	0.000	0.000
	(0.017)	(0.016)	(0.018)
Reason 12	0.006	0.009	0.005
	(0.080)	(0.093)	(0.073)
Reason 13	0.495	0.534	0.476
	(0.500)	(0.499)	(0.499)
Age	33.508	32.513	33.985
	(7.505)	(7.748)	(7.338)
Female	0.271	0.288	0.263
	(0.445)	(0.453)	(0.440)
Married	0.725	0.674	0.749
	(0.447)	(0.469)	(0.433)
Education			
Literate – No Degree	0.010	0.012	0.010
	(0.101)	(0.107)	(0.098)
Illiterate – No Degree	0.005	0.004	0.005
	(0.069)	(0.070)	(0.069)
Primary School	0.556	0.554	0.558
	(0.497)	(0.497)	(0.497)
High School	0.303	0.294	0.307
	(0.459)	(0.455)	(0.461)
2-Year College	0.049	0.054	0.047
	(0.216)	(0.225)	(0.211)
4-Year College	0.073	0.079	0.070
	(0.261)	(0.270)	(0.256)
Masters	0.003	0.003	0.003
	(0.054)	(0.054)	(0.054)
PhD	0.000	0.000	0.000
	(0.010)	(0.009)	(0.010)
Observations	1,797,844	582,009	1,215,835

Note: The sample consists of 1,797,844 individuals who are benefit takers between 2002 and 2012. 582,009 are entitled to 6-month UI benefit period and 1,215,835 of them are entitled to 8-month UI benefit period. The benefit takers in the sample are between the ages of 16 to 65 and have information regarding UI premium days and UI benefit duration and the outcome variables.

are superimposed over outcome averages. The graphical presentation shows that there is a clear evidence of discontinuity in the outcome variables at the cutoff point of 900-paid-premium-days. It implies that factors other than the assignment itself are not playing a role explaining the association. Thus, one may attribute this jump to the treatment. It suggests that estimation of the impact of UI generosity on these outcomes would yield a causal relationship.

4.5. RESULTS

4.5.1. Baseline Results

This section presents the baseline estimation results of the impact of UI benefit generosity on unemployment duration and other outcome variables. Results are presented in Table 4.3. The estimated coefficients are obtained from local linear regressions that are specified as in equation (1). For all estimation equations, the bandwidth is 60-premium-days. The outcome variables, other than unemployment duration, are measured in the first six-month period following the job loss.

The results in column (1) suggest that unemployment duration is forty-one-days longer among benefit takers who are entitled to 8-month benefit period compared to benefit takers who were entitled to 6-month benefit period. 2-month extended benefit recipiency increases the duration of unemployment for almost one and a half months. In other words, one additional week of potential unemployment benefit period leads to 0.7 weeks increase in compensated unemployment duration. For the US, studies find that one additional week of unemployment benefit period leads to 0.08-0.2 weeks longer unemployment duration (Schwartz, 2013; Ehrenberg and Oaxaca, 1976; Moffitt, 1985; Katz and Meyer, 1990). Some studies find no effect of UI benefit generosity on unemployment duration (Card and Levine, 2000). Lalive (2008) and Lalive and Zweimuller (2004) find that additional week of unemployment benefits lead to 0.06-0.09 weeks longer unemployment periods in Austria. Ham and Rea (1987) show that the impact of one additional week of UI benefit is 0.26-0.33 weeks in Canada, which is higher, compared to

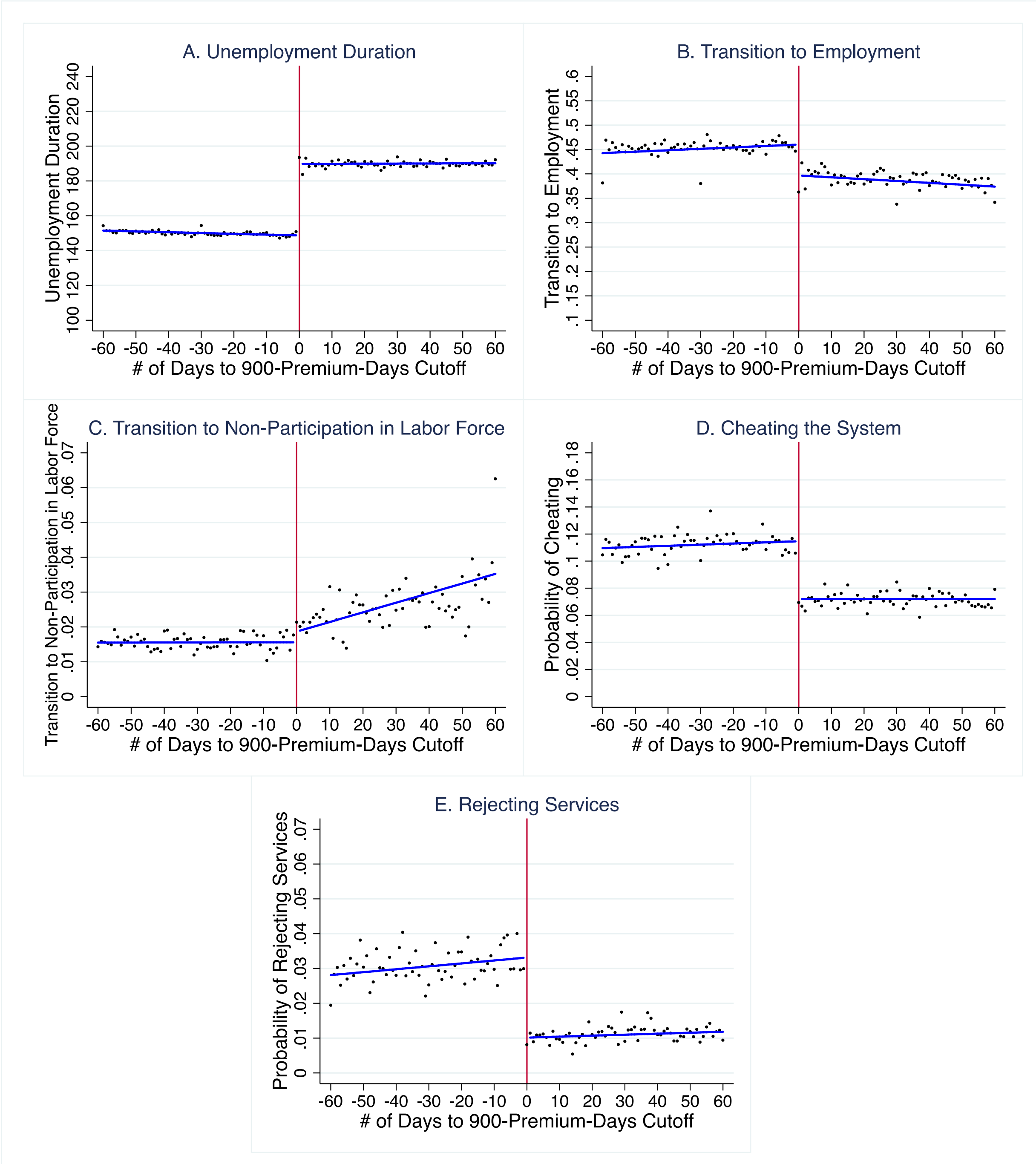

Figure 4.5
The Effect of Unemployment Insurance Benefit Generosity on Outcomes

Note: Each panel shows the unconditional means for outcome variables by each value of the running variable, paid-premium-days. Solid lines are fitted values of outcome from a local linear regression with a bandwidth of 60 days. If the benefit taker's premium days are less than 900-days she is entitled to 6-month UI benefit period. If her premium days are greater than 900-days, the benefit taker is entitled to 8-month benefit period. The cutoff is normalized so that the zero represents 900 paid-premium-days.

Table 4.3
The Impact of UI Benefit Generosity on Unemployment Duration, Transition to Employment and Non-Participation, Probability of Cheating and Rejecting Services
Local Linear Regressions

	Unemployment Duration	Transition to Employment	Transition to Non-Participation	Cheating	Rejecting Services
	(1)	(2)	(3)	(4)	(5)
PD>900	41.112***	-0.063***	0.003	-0.043***	-0.023***
	(0.916)	(0.009)	(0.003)	(0.005)	(0.002)
Observations	450,441	392,599	274,919	303,274	281,919
$PD_0 - 60$	198,862	192,843	195,889	119,189	109,176
$PD_0 + 60$	251,579	199,756	79,030	184,085	172,743

Note: Estimated standard errors, clustered on year and premium days, are displayed in parentheses. Estimates are based on local linear regression with a bandwidth of 60 days. The coefficients show the effect of UI generosity on outcomes. If the benefit taker's premium days are less than 900-days s/he is entitled to 6-month UI benefit period. If her/his premium days are greater than 900-days, the benefit taker is entitled to 8-month benefit period. Regression equations do not include worker characteristics, year effects, and region or industry effects. * 10%, ** 5%, ***1%.

European and the US experiences. The impact of UI generosity on unemployment duration is almost four times greater for Turkey compared to the US.

Column (2) shows the estimated discontinuity for the probability of transition to employment, i.e. probability of finding a job. The probability of finding a job for the benefit takers who are entitled to the extended UI benefits is lower. In other words, probability of finding a job decreases by six-percentage point by additional two months of UI benefit period. This result is lower than the findings in the studies investigating the impact of UI benefit generosity on probability of finding a job for the US, Germany and Austria. For example, Card, Chetty and Weber (2007) finds that 10 weeks increase in the potential benefit duration leads to 5-9% decrease in probability of finding a job. Similarly, Lalive and Zweimuller (2004) show that a 179 weeks increase in the UI benefit duration decreases the probability of finding a job by 17%

(equivalent to 7.2% decrease, by two months of extended UI benefits). For Germany, Caliendo, Tatsiramos and Uhlendorff (2013) shows that probability of finding a job decreases by 7.6% (men) and 8% (women) by additional two months of benefit period. The results suggest that benefit takers in Turkey are experiencing longer unemployment durations compared to workers in developed countries. However, the negative impact of UI generosity on probability of finding a job is lower than of those countries. Another reason of leaving unemployment is entering non-participation in the labor force. Column (3) suggests that UI benefit generosity has no impact on the probability of transition to non-participation in labor force. Carling, Edin, Harkman and Holmlund (1996) find that probability of transition to non-participation is lower among benefit recipients in Sweden. In addition, van den Berg (1990) finds a negative impact for Netherlands. The coefficient of benefit generosity has a positive sign in this study, implying that benefit generosity increases the probability of transition to non-participation. However, it is not statistically significant.

Two other outcomes, which are not available in other studies, are probability of cheating the system and rejecting services provided by the Agency. For benefit takers, receiving UI benefits makes unemployment period less costly both financially and emotionally. Some of the lost income is compensated by the benefit and also job search process might be less stressful due to this support. The UI benefit payments are not high in Turkey. As it is mentioned above, the minimum a benefit taker can be paid (replacement rate) is 40-percent of her earnings. There is also an upper limit, which is 80-percent of the minimum wage in the market. However, for some benefit takers, even this amount might be too high to give up when a wage-earning job opportunity arrives. Receiving benefits and also working in a wage-earning job at the same time might be tempting. If benefit takers are caught exploiting UI benefits in this way, it is considered as cheating the UI system. More generous UI benefits increase the opportunity cost of cheating the system. On the other hand, if the benefit taker is not caught, they can exploit the system for longer periods. Results in column (4) shows that, on average, benefit takers weigh the opportunity cost of cheating more heavily than possibility of exploiting the system. 2-months more generous Unemployment Insurance benefits lead to four-percentage points lower probabilities of cheating the system.[41]

ISKUR provides trainings to help benefit takers gain/develop skills and it also assists them to find a job. If the benefit taker rejects the services the Agency provides, i.e. rejects trainings, not attending to trainings, rejects suggested jobs, her UI benefits are cut. Results presented in column (5) show that the probability of rejecting the Agency's help is lower for the treated group. The probability of rejecting services of the Agency is two-percentage point lower for the benefit takers who are entitled to longer periods of UI benefit periods. As the UI becomes more generous, the opportunity cost of rejecting services increases for benefit takers. For example, assume that a benefit taker starts on trainings provided by the Agency in her fourth month of UI benefit recipiency. If the worker attends to courses for a month and then stops attending, the Agency cuts UI benefits. If the worker was entitled to 6-month period, she loses a month of UI benefits. However, if she is entitled to 8-months UI benefits, then she loses three months of UI benefits. In addition, if she rejects these services, she will not be able to benefit from other services like job search assistance the Agency provides.

[41] In other words, one additional potential week of UI benefits lead to 0.005-percentage point decrease in the probability of cheating the UI system.

4.5.2. Results by Gender and Marital Status

Turkey is a developing country where female labor force participation is very low. In 2012, the female labor force participation is approximately 30-percent while male participation rate is 71-percent.[42] Thus, the female labor-supply decisions, and decisions during UI benefit recipiency might be different than of their male counterparts. In addition, due to child-bearing/rearing decisions, female labor market experience might be different than males. During the benefit recipiency, for example, a female benefit taker might decide to have a baby.

Table 4.4, Panels A and B show the estimation results for women and men, respectively. On average, more generous UI benefits lead to longer unemployment durations for female benefit takers (column 1). There is no difference in terms of probability of finding a job (column 2). Column (3) shows that non-participation increases with UI generosity for females. UI benefit payments might serve as income source to females who would have exited the labor force in the absence of benefits. She might stop looking for a job, but still pretend to be in the labor force. Increase in generosity leads to lower probability of cheating the UI system for male benefit takers (column 4). This result suggests that for male benefit takers the opportunity cost is higher than female benefit takers.

Moreover, decisions of a married or a single benefit taker might be different. A married benefit taker might be able to afford to stay unemployed for longer periods compared to a single benefit taker. Single benefit takers do not have the support of the husband/wife to compensate for the income loss. Hence, her job search process might be more aggressive than a married benefit taker's. Results are shown in Table 4.4, Panel C for married benefit takers and in Panel D in the same table for single benefit takers. Married benefit takers stay unemployed for three more days

[42] http://tuik.gov.tr

Table 4.4
The Impact of UI Benefit Generosity on Unemployment Duration, Transition to Employment and Non-Participation, Probability of Cheating and Rejecting Services by Gender and Marital Status- Local Linear Regressions

		Transition to			
	Unemployment Duration	Employment	Non-Participation	Cheating	Rejecting Services
	(1)	(2)	(3)	(4)	(5)
Panel A: Female					
PD>900	48.411***	-0.068***	0.008***	-0.020***	-0.021***
	(0.804)	(0.010)	(0.002)	(0.004)	(0.002)
Observations	134,012	121,175	69,837	108,301	105,143
$PD_0 - 60$	57,862	56,558	56,916	43,237	41,887
$PD_0 + 60$	76,150	64,617	12,921	65,064	63,256
Panel B: Male					
PD>900	38.304***	-0.056***	0.000	-0.060***	-0.025***
	(1.214)	(0.011)	(0.003)	(0.006)	(0.002)
Observations	316,429	271,424	205,082	194,973	176,776
$PD_0 - 60$	141,000	136,285	138,973	75,952	67,289
$PD_0 + 60$	175,429	135,139	66,109	119,021	109,487
Test of the Coefficients	***	-	*	***	**
Panel C: Married					
PD>900	41.731***	-0.070***	0.008**	-0.045***	-0.021***
	(0.965)	(0.009)	(0.003)	(0.005)	(0.002)
Observations	319,641	279,980	191,828	217,254	201,901
$PD_0 - 60$	136,708	133,534	134,835	82,943	75,826
$PD_0 + 60$	182,933	146,446	56,993	134,311	126,075
Panel D: Single					
PD>900	39.581***	-0.045***	-0.008***	-0.038***	-0.027***
	(1.156)	(0.012)	(0.002)	(0.007)	(0.003)
Observations	130,800	112,619	83,091	86,020	80,018
$PD_0 - 60$	62,154	59,309	61,054	36,246	33,350
$PD_0 + 60$	68,646	53,310	22,037	49,774	46,668
Test of the Coefficients	**	***	***	-	***

Note: Estimated standard errors, clustered on year and premium days, are displayed in parentheses. Estimates are based on local linear regression with a bandwidth of 60 days. The coefficients show the effect of UI generosity on outcomes. If the benefit taker's premium days are less than 900-days s/he is entitled to 6-month UI benefit period. If her/his premium days are greater than 900-days, the benefit taker is entitled to 8-month benefit period. "Test of the Coefficients" is the test of the hypothesis that the coefficient of UI benefit generosity is the same across groups. Regression equations do not include worker characteristics, year effects, and region or industry effects. * 10%, ** 5%, ***1%.

on average compared to single benefit takers (column 1). In addition, married benefit takers who are entitled to extended benefits have a lower probability of finding a job compared to single benefit takers (column 2). These results suggest that, apart from the UI benefit, married benefit takers are using the UI benefits longer because of the possible spousal support. One interesting result is the different sign on the coefficient of the impact of UI generosity on non-participation in labor force for the married and single benefit takers (column 3). Married benefit takers might be able to afford to leave the labor force with more generous benefits. More generous UI benefits might increase the labor force attachment for single benefit takers because they do not have spousal support in case of an involuntary job loss.

4.6. ROBUSTNESS CHECKS

This section provides several robustness checks. First, local linear regressions are estimated with smaller and larger bandwidth selections. Second, I check the sensitivity of results to the functional form by employing higher order polynomials. Last, results from parametric analysis are provided.

4.6.1. Adding Covariates and Bandwidth Selection

I have shown above that benefit taker characteristics are balanced around the 900-paid-premium-days cutoff. One additional way to check the robustness of results to predetermined characteristics is adding them into the regression equation. The results are shown in Table 4.5. It can be concluded that results are robust to inclusion of the benefit taker characteristics. It is also supportive evidence that benefit taker characteristics are balanced around the 900-paid-premium-days cutoff.

Table 4.5
The Impact of UI Benefit Generosity on Unemployment Duration, Transition to Employment and Non-Participation, Probability of Cheating and Rejecting Services
Local Linear Regressions
Benefit Taker Characteristics are Controlled for

		Transition to			
	Unemployment Duration	Employment	Non-Participation	Cheating	Rejecting Services
	(1)	(2)	(3)	(4)	(5)
PD>900	40.473***	-0.045***	0.002	-0.044***	-0.023***
	(0.542)	(0.004)	(0.002)	(0.002)	(0.001)
Observations	450,441	392,599	274,919	303,274	281,919
$PD_0 - 60$	198,862	192,843	195,889	119,189	109,176
$PD_0 + 60$	251,579	199,756	79,030	184,085	172,743
Characteristics	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes
Region Effects	Yes	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	Yes	Yes

Note: Estimated standard errors, clustered on year and premium days, are displayed in parentheses. Estimates are based on local linear regression with a bandwidth of 60 days. The coefficients show the effect of UI generosity on outcomes. If the benefit taker's premium days are less than 900-days s/he is entitled to 6-month UI benefit period. If her/his premium days are greater than 900-days, the benefit taker is entitled to 8-month benefit period. The benefit taker characteristics include age, marital status, gender and education. * 10%, ** 5%, ***1%.

As mentioned above in the identification section, bandwidth selection is a crucial step of estimating local linear regression. When choosing a larger or smaller bandwidth, there is a trade of between precision and bias. If the bandwidth is small the estimated treatment effect will be less biased even if the correct functional form over the running variable is not linear. On the other hand, if it is too large, then linear specification assumption will be more likely wrong. The estimated coefficients of the UI generosity might be biased with misspecification in large bandwidth selections. However, estimated coefficient becomes more precise because there are more observations utilized. I calculate optimal bandwidths for each outcome by using optimal bandwidth selection procedures introduced by Calonico, Cattaneo and Titiunik (2014) and

Imbens and Kalyanaraman (2012). The optimal bandwidths produced by each of these two procedures are presented in the Table C.1. I round the optimal bandwidths to integers. The results are presented in Table 4.6. Apart from a significant coefficient of non-participation in labor force for a smaller bandwidth, results are similar to the ones presented in Table 4.3. Evidence shows that results are not sensitive to alternative bandwidth selections.

Table 4.6
The Impact of UI Benefit Generosity on Unemployment Duration, Transition to Employment and Non-Participation, Probability of Cheating and Rejecting Services
Local Linear Regressions
with Optimal Bandwidth Selections

		Transition to			
	Unemployment Duration	Employment	Non-Participation	Cheating	Rejecting Services
	(1)	(2)	(3)	(4)	(5)
PD>900	40.698***	-0.064***	0.005***	-0.043***	-0.023***
	(0.879)	(0.010)	(0.001)	(0.005)	(0.002)
CCT Optimal Bandwidth	64	41	44	46	48
PD>900	40.520***	-0.064***	0.003	-0.038***	-0.022***
	(0.865)	(0.009)	(0.003)	(0.004)	(0.002)
IK Optimal Bandwidth	66	54	61	71	71

Note: Estimated standard errors, clustered on year and premium days, are displayed in parentheses. Estimates are based on local linear regressions with the optimal bandwidths. The coefficients show the effect of UI generosity on outcomes. If the benefit taker's premium days are less than 900-days she is entitled to 6-month UI benefit period. If her premium days are greater than 900-days, the benefit taker is entitled to 8-month benefit period. Regression equations do not include worker characteristics, year effects, and region or industry effects. * 10%, ** 5%, ***1%.

4.6.2. Higher Order Polynomials and Parametric Estimation

The choice of functional form is an important issue in regression discontinuity design because misspecification leads to bias in the treatment effect (Lee and Lemieux 2010). In this section, I test whether different functional forms provide robust results. I also show these results with alternative bandwidth selections. Table 4.7 provides local linear regression estimates up to polynomial degree of three with bandwidths of 30, 60 and 90 paid-premium-days. In addition, results where coefficient of UI generosity is assumed to be the same on both sides of the threshold are provided (columns 1, 3 and 5). Results are similar to the ones obtained from the main specification.

The last robustness check is to obtain estimated coefficients of UI benefit generosity with parametric models. In application of RD design, parametric and non-parametric approaches are considered as complements. Thus, I present the results from parametric approach in Table 4.8. Results are very similar to the ones obtained by local linear regressions. It suggests that low order polynomial is a good approximation for the functional form of the running variable. Several robustness checks implemented in this section suggest that results obtained in the main specification defined by equation [1] and presented in Table 4.3 are robust to alternative model specifications and bandwidth selections. Models with interaction terms allow the coefficient of benefit generosity to be different below and above the 900-paid-premium-days cutoff. The highest polynomial order is degree of three. There are very slight changes in the coefficient of benefit generosity for each outcome variable. Statistical significance and the sign do not change for any of the outcome variables accept non-participation in the labor force. The coefficient of benefit generosity for non-participation in the labor force seems to be sensitive to bandwidth selections.

4.7. CONCLUSION

Using a unique data obtained from Turkish Employment Agency, I analyze the impact of UI benefit generosity on unemployment duration, transition to employment or non-participation

Table 4.7
The Impact of UI Benefit Generosity on Unemployment Duration, Transition to Employment and Non-Participation, Probability of Cheating and Rejecting Services
Local Linear Regressions
Different Bandwidth Selections and Polynomial Degrees

Dependent Variable	Linear (1)	Linear Interaction (2)	Quadratic (3)	Quadratic Interaction (4)	Cubic (5)	Cubic Interaction (6)
Unemployment Duration						
PD>900; h=30	40.958***	41.201***	41.216***	41.304***	41.618***	42.076***
	(1.488)	(1.382)	(1.415)	(2.119)	(2.069)	(2.785)
Observations	224,311	224,311	224,311	224,311	224,311	224,311
PD>900; h=60	40.880***	41.112***	41.105***	41.056***	41.079***	41.512***
	(0.970)	(0.916)	(0.925)	(1.467)	(1.365)	(2.009)
Observations	450,441	450,441	450,441	450,441	450,441	450,441
PD>900; h=90	40.224***	40.571***	40.536***	40.464***	40.034***	42.328***
	(0.766)	(0.727)	(0.732)	(1.157)	(1.059)	(1.605)
Observations	691,034	691,034	691,034	691,034	691,034	691,034
Employment						
PD>900; h=30	-0.066***	-0.068***	-0.067***	-0.068***	-0.071***	-0.082***
	(0.013)	(0.013)	(0.013)	(0.019)	(0.018)	(0.026)
Observations	195,579	195,579	195,579	195,579	195,579	195,579
PD>900; h=60	-0.062***	-0.063***	-0.063***	-0.066***	-0.066***	-0.074***
	(0.009)	(0.009)	(0.009)	(0.014)	(0.012)	(0.018)
Observations	392,599	392,599	392,599	392,599	392,599	392,599
PD>900; h=90	-0.061***	-0.062***	-0.062***	-0.057***	-0.054***	-0.079***
	(0.007)	(0.007)	(0.007)	(0.011)	(0.010)	(0.015)
Observations	601,524	601,524	601,524	601,524	601,524	601,524
Non-Participation						
PD>900; h=30	0.005***	0.005***	0.005***	0.005*	0.005**	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Observations	138,223	138,223	138,223	138,223	138,223	138,223
PD>900; h=60	0.006***	0.003	0.003	0.008***	0.007***	0.001
	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Observations	274,919	274,919	274,919	274,919	274,919	274,919
PD>900; h=90	0.010***	0.008***	0.009***	0.004*	0.006***	0.004**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Observations	414,168	414,168	414,168	414,168	414,168	414,168

(Table 4.7 Continued)

Dependent Variable	Linear	Linear Interaction	Quadratic	Quadratic Interaction	Cubic	Cubic Interaction
	(1)	(2)	(3)	(4)	(5)	(6)
Cheating						
PD>900; h=30	-0.044***	-0.043***	-0.043***	-0.036***	-0.039***	-0.045***
	(0.006)	(0.007)	(0.007)	(0.010)	(0.008)	(0.014)
Observations	150,618	150,618	150,618	150,618	150,618	150,618
PD>900; h=60	-0.042***	-0.043***	-0.043***	-0.041***	-0.043***	-0.040***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.006)	(0.010)
Observations	303,274	303,274	303,274	303,274	303,274	303,274
PD>900; h=90	-0.037***	-0.038***	-0.038***	-0.041***	-0.039***	-0.046***
	(0.004)	(0.004)	(0.004)	(0.006)	(0.005)	(0.008)
Observations	467,831	467,831	467,831	467,831	467,831	467,831
Rejecting Services						
PD>900; h=30	-0.024***	-0.024***	-0.024***	-0.023***	-0.024***	-0.024***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.005)
Observations	139,855	139,855	139,855	139,855	139,855	139,855
PD>900; h=60	-0.023***	-0.023***	-0.023***	-0.023***	-0.024***	-0.026***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)
Observations	281,919	281,919	281,919	281,919	281,919	281,919
PD>900; h=90	-0.021***	-0.021***	-0.021***	-0.023***	-0.022***	-0.026***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Observations	435,785	435,785	435,785	435,785	435,785	435,785

Note: Estimated standard errors, clustered on year and premium days, are displayed in parentheses. Estimates are based on local linear regression with a bandwidth of 60 days. The coefficients show the effect of UI generosity on outcomes. If the benefit taker's premium days are less than 900-days s/he is entitled to 6-month UI benefit period. If her/his premium days are greater than 900-days, the benefit taker is entitled to 8-month benefit period. Regression equations do not include worker characteristics, year effects, and region or industry effects. * 10%, ** 5%, ***1%.

Table 4.8
The Impact of UI Benefit Generosity on Unemployment Duration, Transition to Employment and Non-Participation, Probability of Cheating and Rejecting Services
Parametric Regressions
Different Polynomial Degrees

	Linear (1)	Linear Interact. (2)	Quadratic (3)	Quadratic Interact. (4)	Cubic (5)	Cubic Interact. (6)
Unemployment Duration						
PD>900	43.610***	42.909***	42.616***	40.770***	40.708***	40.480***
	(0.612)	(0.535)	(0.517)	(0.807)	(0.780)	(1.096)
Observations	1,799,261	1,799,261	1,799,261	1,799,261	1,799,261	1,799,261
Transition to Employment						
PD>900	-0.086***	-0.082***	-0.081***	-0.067***	-0.070***	-0.056***
	(0.005)	(0.005)	(0.005)	(0.008)	(0.007)	(0.010)
Observations	1,526,442	1,526,442	1,526,442	1,526,442	1,526,442	1,526,442
Transition to Non-Participation						
PD>900	0.010***	0.007***	0.007***	0.010***	0.009***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Observations	969,652	969,652	969,652	969,652	969,652	969,652
Cheating						
PD>900	-0.037***	-0.039***	-0.040***	-0.042***	-0.041***	-0.038***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.006)
Observations	1,218,953	1,218,953	1,218,953	1,218,953	1,218,953	1,218,953
Rejecting Services						
PD>900	-0.019***	-0.019***	-0.020***	-0.022***	-0.021***	-0.023***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Observations	1,141,736	1,141,736	1,141,736	1,141,736	1,141,736	1,141,736

Note: Estimated standard errors, clustered on year and premium days, are displayed in parentheses. Estimates are based on local linear regression with a bandwidth of 60 days. The coefficients show the effect of UI generosity on outcomes. If the benefit taker's premium days are less than 900-days s/he is entitled to 6-month UI benefit period. If her/his premium days are greater than 900-days, the benefit taker is entitled to 8-month benefit period. Regression equations do not include worker characteristics, year effects, and region or industry effects. * 10%, ** 5%, ***1%.

in labor force, cheating the UI system and rejecting services of the Agency. I find that UI generosity leads to longer unemployment durations. To be specific, one additional week of UI benefits increases the unemployment duration by 0.7 weeks. This impact is greater than the impact of UI generosity in developed countries such as the US, Germany and Austria. Compared to the UI systems in the developed countries, the system in Turkey is relatively young. In addition, the unemployment rates are higher in Turkey. With higher unemployment rates, the probability of job offers coming might be lower. Thus, it might lead to longer unemployment duration periods. Additionally, benefit takers might be accepting the first offer they get due to high unemployment. However, decreased cost of unemployment with the benefit recipiency might create an incentive for benefit takers to search for jobs that are a best match for their skills or jobs that pay higher wages. In other words, it might change the job search behavior.

In addition to unemployment duration, I investigate the impact of generosity on transition from unemployment to employment and transition from unemployment to non-participation in labor force. I find evidence that UI generosity decreases the probability of transition to employment. To be specific, UI generosity decreases probability of finding a job in the first six-month period by six-percentage points. The impact is lower than the evidence on the impact of UI generosity on transition to employment shown for developed countries. Benefit takers' reservation wage might be increasing with the recipiency of the benefits. Thus, they might reject the job offers coming for jobs that would offer higher wages. In addition, the UI generosity does not have an effect on the probability of transition to non-participation labor force.

There are two outcomes measuring the behavior of benefit takers during the UI benefit recipiency. From the reasons UI benefit is stopped, I measure whether a benefit taker tries to cheat the system and rejects the services of the Agency. If the benefit taker starts working in a wage-earning job while still receiving UI benefits, her benefits are stopped. It might be tempting for workers to accept the first job offer arriving and not reporting the transition to employment to the Agency. Thus, the worker might actually accept a job that pays lower than her reservation wage since UI benefit is compensating for the difference. However, it is only for a short period of time since UI benefit period is limited. Moreover, if caught, she will end up working in a job that pays lower than her reservation wage and pay the extra benefit amount utilized back with the legal interest. In other words, this decision is risky. I find evidence that UI generosity decreases the probability of benefit takers' cheating the UI system. It suggests that benefit takers put more weight on the opportunity cost of cheating the UI system than the possibility of exploiting the system.

The UI premiums collected from the workers are used to finance the trainings and job finding services. The purpose of these services is to provide support for the benefit takers and help them leave unemployment for employment. In addition, these services might help benefit taker not only to find "a" job, but also find one that fits her skill sets best. If the worker rejects trainings or rejects the jobs that are arranged by the Agency, the UI benefits are stopped. Benefit takers might find the trainings provided not necessary if they do not understand the benefits these trainings might bring in the labor force. In addition, they might reject the jobs arranged by the Agency because they might think the wage is lower than their reservation wage. However, the cost of rejecting these job offers is being in the state of uncompensated unemployment. The Agency arranges jobs that are at least paying as well as the previous job. Thus, motivation for rejection might be different. I find evidence that more generous UI benefits decrease the probability of rejecting the services of the Agency.

The results are robust to several sensitivity checks. First, the benefit taker characteristics are included in the model. If the benefit takers around the cutoff are different from each other in terms of predetermined characteristics, then, the impact of UI benefit generosity measured at the cutoff cannot be attributed to the generosity only. However, including the benefit characteristics into the main specification does not alter the coefficient of the UI benefit generosity. It suggests that the results in the main specification show the causal impact of UI benefit generosity on outcomes. Second, I show results with different bandwidth selections and polynomial degrees. Third, I present results from parametric estimations. The robustness checks provide evidence that the results obtained from local linear regressions with 60-paid-premium-days are not sensitive to alternative model specifications and bandwidth selections.

Although it is not possible to observe benefit takers' entire work history, this unique data provides information on the unemployment duration, labor market transitions (transition to employment or non-participation in labor force) within the first six-months of potential benefit recipiency period. It would be a full picture of the impact of UI generosity on labor market outcomes if the data were to include information on the next job and job search activities. Thus, I cannot claim the impact of extended benefits or UI generosity is good or bad for the workers or the society. However, the results suggest that with more generous benefits, benefit takers do not engage in risky activities such as cheating the UI system or reject the services of the Agency. Thus, providing more generous benefits would help reduce the probability of the system being exploited.

It would be interesting to see the long-run impact of UI generosity on unemployment duration. However, it should be kept in mind that UI benefit is a temporary relief, not a permanent one. The sort-term nature of the UI system in Turkey seems to be affecting unemployment duration and labor market transitions in the short-run. Some of the increase in the short-run unemployment duration (Figure 1, Panel A) might be attributed to the introduction of the UI benefits in the beginning of 2000s.

CHAPTER 5. CONCLUSION

The three distinct essays in this dissertation investigate different topics in labor economics. In Chapter 2, I investigate the impact of mother's involuntary job loss on her children's academic achievement. I find that mother's job displacement has a negative impact on her children's academic achievement. The impact of job displacement on test scores is different for single mother and married mother samples. The job displacement of a single mother affects both math and reading scores negatively. To be specific, the math score is twenty-one-percent of a standard deviation and reading score is twenty-three-percent of a standard deviation lower for the children of single displaced mothers compared to children whose mothers are single and were not displaced. There is no evidence that a married mother's job displacement has an effect on test scores.

In order to examine the exogeneity of the mother's job displacement and the causality of the results, a falsification test and selection on observables strategy are implemented and results with child fixed-effects are presented. If the mother is self-selecting herself into plants that are more likely to close down, then the evidence suggesting a negative impact of job displacement on test scores might be measuring productivity differences or unobserved differences in mother characteristics, but not the effect of the job displacement. Falsification test suggests that plant closure may be an exogenous event and results from the Oster (2015)'s strategy show that results are causal, at least for the single mother sample. Controlling for child fixed-effects, I find that estimated impact of displacement decreases for both test scores. The displacement coefficient is negative for both scores but only significant for the reading score.

The two possible channels, income and child's behavioral problems, through which job displacement might affect the child's test scores are investigated in this chapter. Job displacement of the mother has a negative effect on both family income and mother income, and also on the child's behavioral problems for the single mother sample. In order to investigate whether mother income and child's behavioral problems are channels linking mother's job displacement and child's test scores, mother income and overall BPI scores are added to the estimation equation one by one. After adding mother income, coefficients of job displacement decrease for both test scores. Coefficients of short run and long run job displacements also decrease for both test scores. For the single mother sample, after controlling for mother income and the overall BPI score, coefficients of job displacement decrease and become statistically insignificant for both test scores. The results suggest that mother income and child's behavioral problems are channels through which mother's job displacement affects math and reading test scores.

In the next chapter, I examine the impact of hair and eye color on the first-job-after schooling. The results show that having blonde hair has a positive impact on the wage-at-the-first-job, particularly for females and whites. The wage at the first job only includes returns to human capital the individual accumulated before entering the labor market. Once the individual starts working, employers would observe the individual's actual productivity which might lead to wage adjustments. Thus, using the wage at-the-first-job would reflect employers' expected productivity and also the employers' preference about working with attractive/beautiful people.

I investigate whether the effect of wage premium due to light hair, blonde/red hair, is still observed if the individual resides in a county where light-hair or dark-hair is a common feature. I utilize three anthropological studies (Coon 1939; Hulse, 1963; and Geipel, 1969) to determine the predominant hair color of each ethnic group. If the majority of the ethnic group's people has blonde/red hair and blue/green eyes, that ethnic group is considered as a "light-featured" ethnic group. However, if the majority of its people have brown/black hair and eyes, then it is considered as a “dark-featured” ethnic group. Then, I link this information with ethnic origin data collected in the 1980 census to measure the color feature of the county. For example, if the share of people of light-featured ethnic origins is greater than fifty-percent, that county is considered as a “light-featured” county and if it is less than fifty-percent, then it is a “dark-featured” county. I find evidence that blonde females residing in counties where brown/black hair is the common feature (dark-featured county) earn more compared to females with brown/black hair and residing in the same county. There is some evidence that individuals with brown/black hair and residing in a light-featured county get a wage penalty compared to their counterparts residing in a dark-featured county.

The choice of location of residence might be affected by some unobserved ethnic and individual characteristics. In return, it affects the labor market conditions and also whether a county is predominantly light or dark featured. If these characteristics affect color feature of the county and the labor market conditions, then the variable measuring the color feature of the county might be endogenous. To investigate the causality of the results, selection on observables and instrumental variable strategies are utilized. State level color feature and color feature of the state measured by the ethnic origins of the children (younger than 16 years of age) are employed as instruments. Both these strategies suggest that the relationship between having blonde/red hair and wage-at-the-first-job might be causal.

In Chapter 4, I examine the impact of unemployment insurance generosity on unemployment duration and labor market transitions for Turkey, a developing country. I find that the unemployment insurance generosity increases unemployment duration by 0.7 weeks and decrease the probability of entering employment by six-percentage points in Turkey. Compared to developed countries such as the US, Germany and Austria, the impact of UI generosity on unemployment duration is greater. It might be due to different labor market structures, size of the informal sector, and history of the UI system. In Turkey, as in many developing countries, size of the informal sector is large and the UI system is young.

I find that benefit generosity has no effect on the probability of entering non-participation in the labor force; however, it leads to a decrease in non-participation in the labor force for single benefit takers. This evidence is in line with the job search theory. The UI benefit might be increasing the reservation wage which leads to lower probabilities of finding a job. In addition, the data allows me to investigate the impact of UI generosity on cheating the system and rejecting services of the Turkish Employment Agency. It might be the case that as the generosity of UI increases the opportunity cost of losing the benefits increases for the benefit taker. Hence, it leads to lower probabilities of cheating and rejecting the services. Indeed, I find evidence that unemployment insurance generosity decreases the probability of cheating the UI system and rejecting the Agency's services.

To investigate the robustness of the results, several sensitivity checks are implemented. The evidence from the frequency distribution of the running variable suggests that the RD design is valid. The discontinuity measured at the cutoff can be attributed to UI generosity if the benefit takers around the cutoff are different from one another in predetermined characteristics. Including benefit taker characteristics does not alter the results. In addition, there is no discontinuity at the cutoff for predetermined benefit taker characteristics. Moreover, results are robust to alternative bandwidth selections and specifications. The evidence from these sensitivity checks suggests that the results are causal.

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APPENDIX A: SUPPLEMENTARY TABLES FOR CHAPTER 2

Table A.1
Definitions of Variables

Variables	Definition
PIAT Achievement Tests	
PIAT-Reading	= Standard Score for Reading Recognition.
PIAT-Math	= Standard Score for Math.
Child Characteristics	
First Born	= 1 if the child is the first born, 0 otherwise.
White	= 1 if White, 0 otherwise.
Female	= 1 if Child is Female, 0 otherwise.
Number of Siblings	= The number of siblings of the child.
Public School	= 1 if Public School, 0 otherwise.
BPI (Total Std. Score)	= Standard Score for Overall Behavioral Problems.
Anti-social	= Standard Score for Anti-social Subscale.
Anxiety/Depression	= Standard Score for Anxiety/Depression Subscale.
Headstrong	= Standard Score for Headstrong Subscale.
Hyperactive	= Standard Score for Hyperactive Subscale.
Dependent	= Standard Score for Dependent Subscale.
Peer Conflict	= Standard Score for Peer Conflict Subscale.
Mother Characteristics	
Job Displacement	= 1 if the mother is displaced due to plant closure within (0-24)-month window prior to the child's test date, 0 otherwise.
Family Income	= Real Monthly Family Income ($) (base year 2000)
Mother Income	= Real Monthly Mother Income ($) (base year 2000)
Non-Mother Income	= Real Monthly Income of all Other Family Members ($) (base year 2000)
Urban	= 1 if Mother is residing in Urban Area, 0 otherwise.
High School or Less	= 1 if Mother is high school graduate or less, 0 otherwise.
Age at Birth	= Mother's age when she gave birth to the child.
Single	= 1 if the mother is single, 0 otherwise.

Table A.2
BPI Subscale Questions

BPI SUBSCALES	
Antisocial	Hyperactive
Child Cheats and tells lies	Child has difficulty concentrating/paying attention
Child bullies or is cruel/mean to others	Child is easily confused/in a fog
Child does not feel sorry after misbehaving	Child is impulsive- acts without thinking
Child breaks thing deliberately	Child has trouble with obsession etc.
Child is disobedient at school	Child is restless, overly active etc.
Child has trouble getting along with teachers	
Anxiety/Depression	Dependent
Child has sudden changes in mood/feelings	Child clings to adults
Child feels/complains no one loves him/her	Child cries too much
Child is too fearful or anxious	Child demands a lot of attention
Child feels worthless or inferior	Child is too dependent on others
Child is unhappy, sad or depressed	
Headstrong	Peer Conflict
Child is rather high strung, tense, nervous	Child has trouble getting along with others
Child argues too much	Child is not liked by other children
Child is disobedient at home	Child is withdrawn, not involved with others
Child is stubborn, sullen, or irritable	
Child has strong temper, loses it easily	

APPENDIX B: SUPPLEMENTARY TABLES FOR CHAPTER 3

Table B.1
Light and Dark Featured Ethnicities- Example from NLSY79 Ethnic Groups

Ethnic Origin	Light/Dark-features	Ethnic Origin	Light/Dark-features
Black	Dark	Chicano	Dark
Chinese	Dark	Mexican	Dark
English	Light	Mexican-American	Dark
Filipino	Dark	Puerto Rican	Dark
French	Dark	Other Hispanic	Dark
German	Light	Other Spanish	Dark
Greek	Dark	Polish	Light
Hawaiian, P.I.	Dark	Portuguese	Dark
Indian-American	Dark	Russian	Light
Asian Indian	Dark	Scottish	Dark
Irish	Dark	Vietnamese	Dark
Italian	Dark	Welsh	Light
Japanese	Dark	American	-
Korean	Dark	Other	-
Cuban	Dark	None	-

Table B.2
Definitions of Variables

Variables	Definition
Individual Characteristics	
Age	Age at the time of First-job.
Female	= 1 if female, 0 otherwise.
White	= 1 if white, 0 otherwise.
Single	= 1 if the individual is single when the first job started, 0 otherwise.
Wage at the First-job	Log of real wage at the First-job R had after school. (2000 prices)
Eye & Hair Color	
Blue/Green/Hazel Eye (Light-Eyes)	= 1 if eye color is Blue, Green, Hazel, Grey, Other, 0 if Brown, Black.
Blonde/Red Hair (Light-Hair)	= 1 if hair color is Blond, Red, Grey, 0 if Brown, Black.
Blue/Green/Hazel Eye & Blonde/Red Hair	= 1 if eye color is blue/green/hazel AND hair color is blonde/red, 0 otherwise.
Brown/Black Eye & Blonde/Red Hair	= 1 if eye color is brown/black AND hair color is blonde/red, 0 otherwise.
Blue/Green/Hazel Eye & Brown/Black Hair	= 1 if eye color is blue/green/hazel AND hair color is brown/black, 0 otherwise.
Brown/Black Eye & Brown/Black Hair	= 1 if eye color is brown/black AND hair color is brown/black, 0 otherwise.
Blue/Green/Hazel Eye & Blonde/Red Hair	= 1 if eye color is blue/green/hazel AND hair color is blonde/red, 0 otherwise.
Father Characteristics	
Less than High School	= 1 if Father has less than High School Education.
High School Graduate	= 1 if Father graduated from High School.
College Graduate	= 1 if Father has college degree.
Master's Degree or more	= 1 if Father has master's degree or more.
Mother Characteristics	
Less than High School	= 1 if Mother has less than High School Education.
High School Graduate	= 1 if Mother graduated from High School.
College Graduate	= 1 if Mother has College Degree.
Master's Degree or more	= 1 if Mother has Master's Degree or more.
County Characteristics	
Light-Featured County	= 1 if the share of individuals of light-featured ethnic origins is greater than 50% in the county, 0 if less than or equal to 50%.
HHI	HHI measured for the county where individual was residing at the year first-job started on 1980 census. anc=ancestry group (e.g. French, German,..) $\sum_{i=1}^{n}\left(\frac{anc_i}{population}\right)^2$

APPENDIX C: SUPPLEMENTARY TABLES AND FIGURES FOR CHAPTER 4

Table C.1
Optimal Bandwidth Selection

Variables	IK	CCT
Predetermined Variables		
Gender	43.11	22.80
Married	48.91	58.61
High School Graduate	51.67	48.62
Daily UI Benefit Amount	58.49	40.27
Outcome Variables		
Unemployment Duration	66.04	63.87
Transition to:		
Employment	53.96	40.77
Non-Participation in the Labor Market	61.03	44.23
Cheating	71.22	45.88
Rejecting Services	71.14	48.40

Note: CCT represents optimal bandwidth selection with Calonico, Cattaneo and Titiunik (2014) and IK represents selection with Imbens and Kalyanaraman (2012).

Table C.2
Frequency of the Running Variable with Different Bandwidths

Bandwidth	Coefficient	Control Mean	P-Value
$PD_0 - 30 < PD_i \leq PD_0 + 30$	-446.79	3,720	0.461
$PD_0 - 60 < PD_i \leq PD_0 + 60$	-280.16	3,590	0.449
$PD_0 - 90 < PD_i \leq PD_0 + 90$	-301.48	3,609	0.233
$PD_0 - 120 < PD_i \leq PD_0 + 120$	-297.16	3,607	0.191
$PD_0 - 150 < PD_i \leq PD_0 + 150$	280.43	3,029	0.327

Note: Coefficient for the frequency of the running variable is estimated by using Local Linear Regressions.

Table C.3
Balance Around the Cutoff with Optimal Bandwidths

	Gender (Female)	Married	High School Graduate	Daily UI Benefit Amount	Predicted Unemp. Duration
	(1)	(2)	(3)	(4)	(5)
Panel A: Optimal Bandwidth *(IK)*					
PD>900	-0.004	0.011	-0.005	-0.033	0.164
	(0.006)	(0.007)	(0.004)	(0.063)	(0.243)
Optimal Bandwidth (h)	*h=43*	*h=49*	*h=52*	*h=58*	*h=27*
N	314,855	358,163	380,516	*424,836*	*195,240*
$PD_0 - h$	142,206	161,187	170,862	*189,586*	*88,658*
$PD_0 + h$	172,649	196,976	209,654	*235,250*	*106,582*
Panel B: Optimal Bandwidth *(CCT)*					
PD>900	0.006	0.012*	-0.005	0.009	0.287
	(0.008)	(0.007)	(0.004)	(0.076)	(0.278)
Optimal Bandwidth (h)	*h=23*	*h=59*	*h=49*	*h=40*	*h=21*
N	*167,215*	*432,729*	*358,130*	*294,204*	*153,677*
$PD_0 - h$	*76,059*	*192,768*	*161,177*	*132,865*	*69,797*
$PD_0 + h$	*91,156*	*239,961*	*196,953*	*161,339*	*83,880*

Note: Estimated standard errors, clustered on year and premium days, are displayed in parentheses. Each coefficient on UI benefit generosity is estimated with local linear regression with the optimal bandwidth. The coefficients show the effect of being entitled to longer UI benefit periods on predetermined characteristics. * 10%, ** 5%, ***1%

Table C.4
Definitions of Variables

Variables	Definition
Unemployed	If the worker is receiving the UI benefits she is considered as unemployed.
<u>Outcome Variables</u>	
Unemployment Duration	The number of days the benefit taker received the unemployment insurance (UI) benefit.
Transition to Employment	= 1 if the benefit taker's UI benefit is stopped because she finds a job within the first 6-month period, = 0 if s/he is unemployed in the first 6-month period.
Transition to Non-Participation in Labor Force	= 1 if the benefit taker's UI benefit is cut within the first 6-month period due to finding a new job (reporting and not reporting cases) or she is unemployed, = 0 if the benefit is stopped due to not being ready to work, retirement, temporarily unable to work and military service.
Cheating the System	= 1 if the benefit taker's UI benefit is stopped within the first 6-month period due to her failure to report a new job with pay, = 0 if s/he is unemployed in the first 6-month period or finds a new job.
Rejecting ISKUR's Services	= 1 if the benefit taker's UI benefit is cut within the first 6-month period because s/he rejected invitation, rejected training, or rejected suggested job, = 0 if s/he is unemployed in the first 6-month period or finds a new job.
<u>Benefit Taker Characteristics</u>	
Number of Paid-Premium Days	The number of days the benefit taker paid UI premiums within last 3 years.
Entitled	Number of Days the benefit taker is entitled to receive UI Benefits.
The Daily UIB	The amount daily UI Benefit the benefit taker received in Turkish Lira. (deflated by CPI, 2003 prices)
The Sum of UIB	The lump-sum amount of UI Benefit Received in Turkish Lira. (deflated by CPI, 2003 prices)
Education	
No Degree and Literate	=1 if the benefit taker has no degree but literate, = 0 otherwise.
No Degree and Illiterate	=1 if the benefit taker is not literate, = 0 otherwise.
Primary School	=1 if the benefit taker has primary school degree (8-year education) , = 0 otherwise.
High School	=1 if the benefit taker is high school graduate, = 0 otherwise.
2-Year College	=1 if the benefit taker has 2-year college degree, = 0 otherwise.
4-Year College	=1 if the benefit taker has 4-year college degree, = 0 otherwise.
Masters	=1 if the benefit taker has a master's degree, = 0 otherwise.
PhD	=1 if the benefit taker has a PhD degree, = 0 otherwise.

(Table 4.2 Continued)

Variable	Definition
Age	Age of the benefit taker.
Female	= 1 if the benefit taker is female, = 0 if male.
Married	= 1 if the benefit taker is married, = 0 if single.
Reasons UI Benefit Stopped	
Reason 1	Not Ready for Work
Reason 2	Rejecting Invitation
Reason 3	Rejecting Training
Reason 4	Started to Receive Retirement Payments
Reason 5	Became Eligible for Retirement Payments
Reason 6	Caught on Working on a Job with Pay
Reason 7	Temporarily Unable to Work
Reason 8	Not Attending to Trainings
Reason 9	Starting to a New Job
Reason 10	Death
Reason 11	Rejecting the Suggested Jobs
Reason 12	Military Service
Reason 13	Entitled Period of UI benefit is Exhausted (Unemployed)

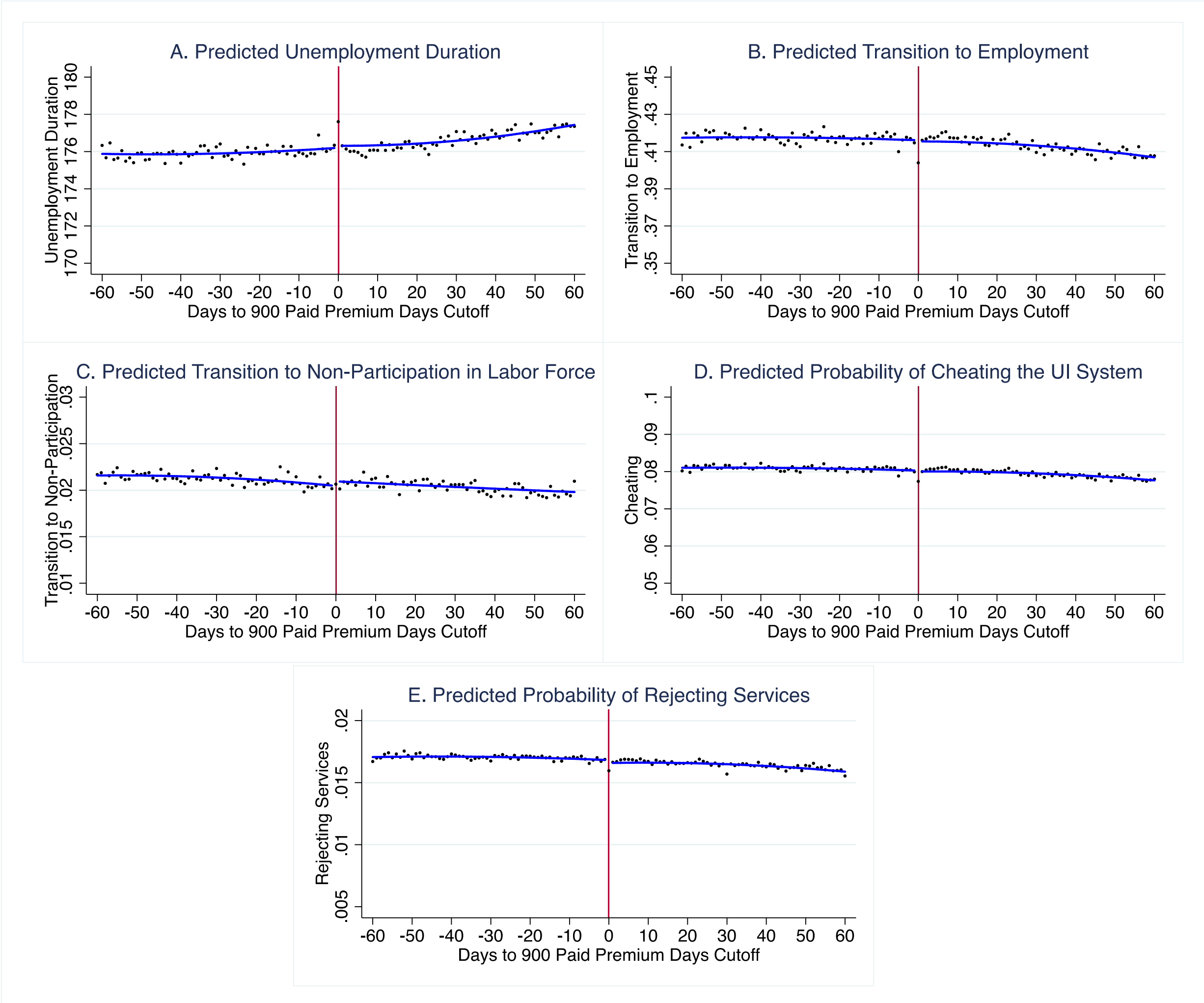

Figure C.1
The Effect of Unemployment Insurance Benefit Generosity on Predicted Outcomes

Note: Each panel shows the mean predicted outcome variable by each value of the running variable, paid-premium-days. Predicted values are generated by regressing each outcome variable on the pre-determined benefit taker characteristics. Then, predicted values are regressed on the running variable to estimate the discontinuity at the threshold. Solid lines are fitted values of predicted outcomes from a local linear regression with a bandwidth of 60 days. If the benefit taker's premium days are less than 900-days s/he is entitled to 6-month UI benefit period. If her/his premium days are greater than 900-days, the benefit taker is entitled to 8-month benefit period.

VITA

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