REPUBLIC OF TÜRKİYE
YILDIZ TECHNICAL UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
DEPARTMENT OF ECONOMICS
PhD PROGRAM IN ECONOMICS

PhD THESIS

THREE ESSAYS ON ECONOMICS OF EDUCATION

SELİN ERDOĞAN
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ADVISOR
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SELİN ERDOĞAN
17729016
ORCID NO: 0000-0001-8903-3068

ADVISOR
PROF. DR. HÜSEYİN TAŞTAN

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ABSTRACT

THREE ESSAYS ON ECONOMICS OF EDUCATION

This thesis, composed of three distinct but interrelated essays, delves into critical aspects of the economics of education within the Turkish context, offering empirical insights and policy implications. The first essay examines factors influencing academic performance among Turkish secondary students in mathematics, science, and reading, using PISA 2018 data. Employing advanced machine learning, it identifies the Boosted Regression Tree as the most accurate predictive model. The results highlight the crucial role of high school program type—general versus vocational—in student achievement. Additionally, the interaction between student-level and school-level factors is emphasized as a key determinant of success across all subjects, providing insights for improving educational outcomes in Türkiye. The second essay addresses school dropout, a challenge to educational and social equity. Using Survival Analysis, it investigates the timing of dropout events across educational levels in Türkiye. Data from the Turkish Statistical Institute highlight increased dropout risks during transitions, particularly from primary to secondary education. The study identifies socio-economic factors—including child labor, parental education, family structure, and regional disparities—that heighten dropout risks, especially in eastern Türkiye. These insights underscore the need for targeted interventions to support at-risk students. The third essay examines the impact of Türkiye's 2012 reform extending compulsory education from 8 to 12 years. Utilizing a Regression Discontinuity Design, it evaluates the reform's effects on educational attainment and labor market outcomes. Data from the Household Labor Force Surveys (2013-2022) indicate that the reform significantly increased years of schooling and high school graduation rates, particularly among the sample consisting of employed individuals. However, its effects on university attainment and labor market outcomes, such as earnings, were mixed and varied by gender. While the reform benefited females more in educational outcomes, its impact on employment and labor force participation was limited, with notable gender disparities. These findings provide insights into the reform's long-term effectiveness and its implications for policy.

Keywords: Educational Data Mining, School Dropout, Survival Analysis, Compulsory Schooling Laws, Regression Discontinuity

ÖZ

EĞİTİM EKONOMİSİ ÜZERİNE ÜÇ MAKALE

Bu tez, birbiriyle ilişkili üç farklı makaleden oluşmakta olup, Türkiye bağlamında eğitim ekonomisinin kritik yönlerine dair ampirik bulgular ve politika önerileri sunmaktadır. İlk makale, PISA 2018 verilerini kullanarak Türk ortaöğretim öğrencilerinin matematik, fen ve okuma alanlarındaki akademik başarılarını etkileyen faktörleri incelemektedir. İleri makine öğrenmesi yöntemlerini kullanarak, En Doğru Tahmin Modeli olarak Yükseltilmiş Regresyon Ağacı belirlenmiştir. Sonuçlar, genel ve mesleki orta eğitim programları arasındaki farkın öğrenci başarısındaki kritik rolünü vurgulamaktadır. Ayrıca, öğrenci düzeyi ve okul düzeyi faktörleri arasındaki etkileşim, tüm derslerdeki başarı için önemli bir belirleyici olarak öne çıkmakta olup, Türkiye'deki eğitim sonuçlarını iyileştirme konusunda önemli bulgular sunmaktadır. İkinci makale, Türkiye'de okul terki olgusunu ele almaktadır. Sağ Kalım Analizi kullanılarak, Türkiye'deki eğitim seviyeleri boyunca okul terk etme olaylarının zamanlaması incelenmiştir. Türkiye İstatistik Kurumu'nun verileri, özellikle ilkokuldan ortaöğretime geçişte, okul terk risklerinin arttığını göstermektedir. Çalışma, çocuk işçiliği, ebeveyn eğitimi, aile yapısı ve bölgesel farklılıklar gibi sosyo-ekonomik faktörlerin, özellikle Türkiye'nin doğu bölgelerinde, okul terk risklerini artırdığını tespit etmektedir. Bu bulgular, risk altındaki öğrencilere yönelik hedefe yönelik müdahalelerin gerekliliğini vurgulamaktadır. Üçüncü makale, Türkiye'nin zorunlu eğitimi 8 yıldan 12 yıla çıkaran 2012 reformunun etkilerini incelemektedir. Regresyon Süreksizlik Tasarımı kullanılarak, reformun eğitim düzeyi ve işgücü piyasası sonuçları üzerindeki etkileri değerlendirilmiştir. Hanehalkı İşgücü Anketleri'nden (2013-2022) elde edilen veriler, reformun özellikle çalışan bireylerden oluşan örneklemde, eğitim süresi ve lise mezuniyet oranlarını önemli ölçüde artırdığını göstermektedir. Ancak, üniversiteye erişim ve işgücü piyasası sonuçları, özellikle gelir açısından, karmaşık ve cinsiyete göre farklılık göstermektedir. Reform, kadınlar için eğitim sonuçlarında daha fazla iyileşme sağlarken, istihdam ve işgücüne katılım üzerindeki etkisi sınırlı kalmış ve önemli cinsiyet farklılıkları ortaya çıkmıştır. Bu bulgular, reformun uzun vadeli etkinliği ve politika üzerindeki etkilerine dair önemli içgörüler sunmaktadır.

Anahtar Kelimeler: Eğitimsel Veri Madenciliği, Okul Terki, Sağ Kalım Analizi, Zorunlu Eğitim Kanunları, Regresyon Süreksizlik Tasarımı

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However, this journey has also been marked by profound loss. The passing of my beloved grandfather and brother-in-law during this time was a source of deep sorrow. Their memories and the values they instilled in me continue to guide my path. This thesis is, in part, a tribute to them and the legacies they have left behind.

Finally, to my son, Timur Mehmet Erdoğan, you are the light of my life. Although you are too young to understand now, your arrival brought boundless happiness and renewed purpose to my life. I hope that one day you will look at this work with pride, knowing that you were a part of this journey.

This thesis is dedicated to my family—those here with me and those who have passed on. It is their love, support, and belief in me that have made this achievement possible.

Selin ERDOĞAN

November, 2024; Istanbul

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LIST OF ABBREVIATIONS

ATE	: Average Treatment Effect
BRT	: Boosted Regression Tree
CART	: Classification and Regression Tree
EDM	: Educational Data Mining
ESCS	: Economic, Social, Cultural Status
HBS	: Household Budget Survey
HLFS	: Household Labor Force Survey
LASSO	: Least Absolute Shrinkage Operator
LATE	: Local Average Treatment Effect
MoNE	: Ministry of National Education
MSE	: Mean Square Error
NEET	: Not in Education, Employment or Training
NUTS	: Nomenclature of Units for Territorial Statistics
OECD	: Organization for Economic Cooperation and Development
PISA	: Programme for International Student Assessment
PV	: Plausible Value
TDHS	: Turkish Demographic Health Survey
TIMSS	: Trends in International Mathematics and Science Study
TURKSTAT	: Turkish Statistical Institute
RDD	: Regression Discontinuity Design
VAT	: Vocational and Technical
WCS	: Working Child Statistics
2SLS	: Two Stage Least Square

1. INTRODUCTION

This thesis examines crucial aspects of the educational landscape in Türkiye, focusing on student performance, school dropout, and the impacts of compulsory schooling educational reform. The three essays collectively contribute to a nuanced understanding of how various factors influence educational outcomes in a developing country context, providing empirical evidence out of robust econometric analyses and policy recommendations that are vital for enhancing educational practices and addressing systemic challenges in Türkiye.

Primary and lower secondary education are crucial for developing individuals' foundational numeracy and literacy skills, serving as a preparation for upper secondary education which plays a significant role by providing the necessary competencies for both the workforce and higher education. This stage of education is pivotal as it represents the first level where individuals acquire essential skills and knowledge that contribute to the development of economic workforce and societal well-being. Adults lacking an upper secondary qualification face significant risks of adverse social and labor market outcomes throughout their lives. Consequently, reducing the proportion of young adults who do not attain an upper secondary qualification has become a priority of governments in many countries. As reported in the OECD's *Education at a Glance 2024*, the proportion of young adults aged 25-34 without upper secondary education has declined between 2016 and 2023 in 28 of the 35 OECD member countries. Although Türkiye is among the countries where this trend has been observed such that it declined from 45% to 30%, it is still 16 percentage points above the OECD average in 2023.

Closely linked to this issue, the phenomenon of youth NEET (Not in Education, Employment, or Training) is widely recognized as detrimental to a nation's economy. It exacerbates the erosion of human capital, resulting in the underutilization of the potential labor force, thereby hindering GDP growth. Moreover, the implications of youth NEET extend beyond collective economic harm to individual detriment. Young individuals who are neither employed nor engaged in education or training are at heightened risk of social exclusion, often living below the poverty line and lacking the requisite skills to improve their economic circumstances. According to the OECD’s *Education at a Glance 2024,* the average NEET rate for people aged 18–24 in most OECD member countries fell from 15.8% to 13.8% between 2016 and 2023, attributed to increased participation in education. Although Türkiye is one of the countries that have experienced a decline in the youth NEET rate, from 33% to 31.1% over the same period, it still remains above the OECD average, marking the highest rate.

Research has shown a strong correlation between educational outcomes and economic growth. Countries that perform well in international student assessment tests like PISA tend to have higher levels of human capital, which is essential for innovation and long-term economic prosperity. According to the most recent PISA results; since 2003, Turkish students have consistently performed below the OECD average in mathematics, science, and reading across the seven PISA assessments in which Türkiye has participated. Türkiye's mean scores in mathematics, science, and reading are 453, 456, and 476, respectively, all of which are below the corresponding OECD averages of 472, 476, and 485 in PISA 2022. Furthermore; while a small proportion of Turkish students are performing at the highest levels (Levels 5 and 6), a significant portion struggles with basic proficiency (below Level 2), especially when compared to OECD averages. For instance, in mathematics, only 4% of Turkish students were top performers, compared to the OECD average of 12%, while 37% were classified as low performers, significantly higher than the OECD average of 24%. Similarly, in reading, 2% of Turkish students reached top performer status, far below the OECD average of 9%, with 36% falling into the low performer category, compared to the OECD average of 23%. In science, 3% of Turkish students achieved top performance levels, against a 7% OECD average, while 35% were low performers, much higher than the OECD average of 21%. In addition to these, while Türkiye has maintained its average score in mathematics and improved its average score in science from PISA 2018 to PISA 2022, it has experienced a decline in its average reading score. Therefore, addressing these disparities is crucial for improving educational outcomes in Türkiye.

Given Türkiye’s current position in the educational sphere, all three essays systematically explore the factors influencing the process of educating individuals and their subsequent integration into the Turkish economy. In order to delve deeper into the subject, this dissertation, composed of three separate essays, aims to address the following key questions.

1. What are the predictors of student achievement in Türkiye? Do student – level or school – level factors (or both) come forward? Which machine learning method has the most predictive accuracy in finding these predictors?
2. How long does it take a Turkish student to drop out of school? Which factors are influential in this duration? How a change in student's demographic or socioeconomic conditions will influence overall grade attainment?
3. What are the impacts of the recent extension of compulsory schooling from 8 to 12 years in Türkiye on educational outcomes, such as years of schooling, high school graduation rates, and university graduation rates, differentiated by gender? Additionally, how has this policy shift influenced labor market outcomes for males and females, including monthly income, hourly wages, employment status, and labor force participation?

Related to the first question, the first essay delves into the determinants of academic performance among Turkish secondary school students in Educational Data Mining framework. This study evaluated the predictive performance of three supervised machine learning methods—Decision Trees, Regularization Models, and Linear Regression—on Turkish secondary school students' academic outcomes in mathematics, science, and reading as measured in PISA 2018. The dataset is divided into an 80% training set and a 20% test set prior to analysis. For each method, 10-fold cross-validation is applied to the training set to estimate the model and determine its optimal hyperparameters. The predictive accuracy of each model is then assessed on the test set using the mean squared error metric. Relatedly, boosted regression tree (BRT) method is evaluated as with the highest predictive accuracy among the methods of multiple linear regression, ridge regression, LASSO, elastic net regression, bagging and random forest regression trees. Study also identifies the most predictive variables that influence student success within Türkiye's highly competitive education system. The essay highlights that students enrolled in general secondary education schools consistently outperform their peers in vocational and technical education, underscoring the need for targeted improvements in the latter. Besides; the top most influential features of Turkish students' achievements are identified as socioeconomic background, number of books at home, use and availability of ICT at both home and school, student's time devoted to learning, emergence of negative behavior at school. This essay contributes to the literature by demonstrating the efficacy of machine learning in educational data mining and by providing recent actionable insights for policymakers aiming to enhance student outcomes in key subject areas.

Related to the second question, the second essay addresses the persistent issue of school dropout, a critical barrier to educational and social equity in Türkiye. This study utilizes survival analysis to investigate the expected duration of schooling for Turkish students of compulsory school age and to identify the key factors influencing dropout risks across various educational levels. By incorporating the timing of dropouts and addressing the unique challenge posed by censored data on school dropout, the study provides a nuanced understanding of the factors at play. The study first estimates and plots Kaplan-Meier survival function (i.e. remaining in education) for the sample as a whole and for different groups based on background characteristics. In addition to visual inspection, Log-Rank test is employed in order to determine whether survival probabilities of different groups are significantly different from each other. Finally, the Cox Proportional Hazards model is utilized to analyze the impact of various factors on school dropout rates among Turkish students of compulsory school age. These factors include child employment, parental education and occupation, family structure, household income, engagement in domestic duties, and demographic variables such as gender, age group, and geographical region within the country. The analysis draws on data from the Turkish Statistical Institute's most recent surveys on Working Child Statistics and the Household Labor Force Survey. The findings reveal that most of the school dropout occurs at grades corresponding to the end of educational levels, with an emphasis on the transition from primary to secondary education. In addition, probability of not having dropout yet is reported to exhibit expected relationships with background characteristics. Children from larger families, those with parents having low levels of educational attainment or being illiterate, those residing in the eastern regions of the country and working children face higher risk of dropping out from school. This essay contributes to the literature by accounting for the peculiarity of school dropout data and estimating the likelihood of students' remaining in education beyond a certain grade level, as well as the influence of various factors on this likelihood. It underscores the critical need for policies that mitigate the adverse effects of socioeconomic disadvantages and regional disparities, which are essential for keeping students engaged in the education system and ensuring their continued participation.

Related to the last question, the third essay examines the impact of Türkiye's 2012 compulsory schooling reform, which extended mandatory education from 8 to 12 years. Employing a Fuzzy Regression Discontinuity Design framework, the study designates treatment status based on year of birth, categorizing individuals born after January 1998 into the treated group. Utilizing data from the Household Labor Force Surveys conducted by the Turkish Statistical Institute between 2013 and 2022, the study analyzes the reform's effects on educational outcomes, including the number of years of schooling completed, high school graduation rates, and university graduation rates, as well as labor market outcomes such as monthly income, hourly wages, employment status, and labor force participation status. The results indicate that the reform significantly increased the number of schooling years attained, particularly for females, and improved high school and university graduation rates among employed individuals. While the reform improved schooling, high school completion, and university degree attainment for employed individuals, these findings do not generalize to the broader sample, including unemployed and out-of-labor-force individuals. In terms of labor market outcomes, the reform has a positive impact on monthly earnings and hourly wages, especially for females and to some extent for males. However, these effects for males are sensitive to the polynomial order of the running variable and the bandwidth selection. The extension of compulsory education from 8 to 12 years had no significant impact on employment and labor force participation, except that university completion increased these probabilities for females. This essay contributes to the literature by exploring the impact of the recent education reform of 2012, which extends the duration of compulsory education to 12 years in Türkiye, on the schooling and labor market outcomes of individuals. While previous research has extensively examined the impacts of the 1997 education reform, the effects of the more recent 2012 education reform have been relatively underexplored in the existing literature.

Together, these essays provide a comprehensive analysis of the factors influencing educational outcomes in Türkiye, from student performance and dropout risks to the broader impacts of systemic reforms. The findings underscore the importance of targeted, evidence-based interventions to improve educational quality and equity over the period of compulsory schooling, offering valuable insights for policymakers and educators in Türkiye and other developing countries facing similar challenges.

The rest of the thesis is organized as follows. Section 2 begins with the first essay, which uses machine learning techniques and the PISA dataset to examine the predictors of student achievement in Türkiye. Section 3 continues with the second essay, investigating school dropout from a novel perspective, focusing on its timing and the determinants of this timing. Section 4 presents the third essay, which analyzes the impact of the 2012 compulsory schooling reform, increasing mandatory years of schooling from 8 to 12 years, on a range of educational and labor market outcomes. Concluding remarks are provided in Section 5. Appendices (if any) and References for each essay are presented at the end of each respective section.

2. PREDICTING STUDENT ACHIEVEMENT: EVIDENCE FROM MACHINE LEARNING APPLICATION TO TURKISH SUBSET OF PISA

2.1. Introduction

Increasing student success is an ultimate goal for academic institutions because education plays an essential role in the development of a modern society. Education in fact has a comprehensive goal in a society, that is raising people who are well-integrated to it. To achieve this integration, it is important for individuals to understand and value societal principles while also developing the skills required for future employment, starting from today. Therefore, public education is a means to serve the young members of the society as being future capable, productive and integrated adults. Well-educated and integrated individuals are expected to contribute more to entities for which they work and hence to countries in which they live because they are more likely to work with increased knowledge and productivity, and consequently be able to generate higher income. Therefore, it is natural to conclude that education functions in a society as promoting not only social well-being but also social welfare.

An important condition for increasing students' success is the determination of factors that are instrumental in students' academic performance. Foreknowledge of students' success elements could support policymakers in attaining the possible highest level of quality education. Such knowledge can be acquired by predicting student performance through using machine learning techniques over educational microdata which has become prominent with recent large-scale educational assessment surveys. If students' probable poor performance is accurately predicted before an upcoming exam through a model, then educators can make the necessary improvements to instructional process beforehand and plan in-time personalized support for those students. The main objective here is having pre-information related to *students at risk*. Instead of one-size-fits-all educational policies which assumes provided that each student is taught the standard curriculum and given instruction, all students are going to achieve equal academic success irrespective of e.g. their socioeconomic status and/or family background etc., making educators and educational policy makers be informed enables better guidance and early intervention. For example, as the role of students' socioeconomic status (as well as endowments at home) and self-efficacy in academic achievement are elements commonly stressed by recent studies using machine learning techniques (Chen et al., 2021; Dong & Hu, 2019; Gabriel et al., 2018; Hu & Peng & Ma,2022; Lee & Lee, 2021; Martinez-Abad & Gamazo & Conde, 2020; Masci et al., 2018; Puah, 2021; She & Lin & Huan,2019; Yoo, 2018 and others), policymakers (and educators) could aim fostering development of self-efficacy in students by channeling more resources to this area, and although at the school level it is harder to mitigate the possible negative influences of lack of home endowments and of low socioeconomic status; school environment can be enriched in terms of arithmetic and literacy (i.e. conducting remedial classes etc.).

Predicting student performance is even more important within an education system which is centralized and characterized by early tracking of students and by highly competitive external exams. Early tracking of students means that, students attend central external exams at early ages, and this corresponds to 13 years olders in Türkiye, which is one of the earliest ones among OECD countries. Besides; during their education life, Turkish students are required to take two important competitive external central exams which are conducted at levels of highschool entrance and university entrance. A Turkish young student takes highschool entrance exam and is placed at a highschool based on his/her success at this exam. The highschool that is placed plays a crucial role at an early stage in the achievement at university entrance exam because students have been classified into different types of high schools based on their abilities and their past academic records. Besides, students in Türkiye has scored lower than the OECD average in mathematics, science and reading subjects in six PISA assessments that Türkiye has attended since 2003. In addition; for PISA 2018 assessment, 3% of Turkish students were top performers in reading subject area meaning that they attained level 5 or 6 whereas this corresponds to 9% in OECD's average. According to PISA, at levels of top performance in reading, students can understand lengthy texts, deal with abstract or counterintuitive concepts, and recognize distinctions between fact and opinion based on implicit cues related to the content. In mathematics, 5% of Turkish students scored at Level 5 or higher (OECD average: 11%) in PISA 2018 assessment. According to PISA, top performers in mathematics can model complex situations mathematically, and can employ, compare and evaluate appropriate problem-solving strategies in dealing with them. In science, 2% of Turkish students were top performers, meaning that they were proficient at Level 5 or 6 (OECD average: 7%). According to PISA, these students are able to creatively apply their knowledge about science to a wide range of situations, including unfamiliar ones. Given that Türkiye's past performance which is on average is below OECD average for all subjects, it is important to explore how to develop further advanced as well as basic literacies of Turkish young in principal subject areas. This thesis aims to contribute to the growing area of research by exploring evidence from a case of developing country with a large per cent of young people and where consecutive educational reforms are inaugurated by local authorities. Accordingly, lessons can be drawn for other developing countries as well as for developed countries.

Future occupational status of young people is highly determined by their current academic records which have been accruing from past. Relatedly, economic and social development is directly linked with student academic performance. Although absorption of newly developed ideas and technologies is possible with basic competency in key areas of literacy, the creation and spread of those require some higher level of individual skills that flourish with education. In other words, students' academic performance plays an important role in producing the best quality graduates who will become workforce of the country therefore accountable of the country's economic and social development. Bearing this in mind, the fact that a large fraction of the whole population of Türkiye consists of young people, predicting student performance at an upcoming exam and taking necessary precautions at individual, school or social level is an important issue in order to ensure that all students are going to realize their best potential in the future. Therefore, predicting academic achievement of students has a role to play in designing and planning scholastic process in order to make it more sensitive and effective. This will enable stakeholders of education process such as policymakers, educators, education researchers, students, and eventually the society not only make predictions but also bring new insights which exist within multiple dimensions of large-scale educational data.

This study represents an effort to identify the optimal predictive model for secondary school student performance in an international assessment using a range of supervised machine learning techniques within the Turkish context. Unlike previous studies that often focus on a single subject, this research encompasses all principal subjects, providing a comprehensive evaluation of student achievement. Additionally, it offers a detailed analysis of how high school type serves as a predictor of performance across these subjects, thus shedding light on the differential effects of school environments on academic outcomes. This work fills a critical gap in the literature by combining advanced predictive analytics with a broad, multi-subject scope, contributing valuable insights to education policy and school-based strategies for improving student achievement in Türkiye.

The remainder of this essay is organized as follows: The next section reviews the literature about concept of Educational Data Mining. Data and descriptive analysis are given in Sections 2.3 and 2.4. Empirical methodology is explained in Section 2.5. Main results from machine learning framework are presented in Section 2.6. Important findings are discussed in Section 2.7. Finally, Section 2.8 concludes with a brief summary.

2.2. Literature Review

The production of education which mainly refers to student academic achievement in terms of outcome as determined by various background characteristics dates back to a study in 1966 named *Equality of Educational Opportunity*, which concluded that school inputs have little influence on student achievement (Coleman et al., 1966). ‘the inequalities imposed on children by their home, neighborhoods and peer environment are carried along to become the inequalities with which they confront adult life at the end of school’ (p. 325). Since then, as more and more data become available and more sophisticated methodological perspectives are introduced, a substantial body of literature has emerged. One strand of literature has attempted to account for sources of differences in student academic achievement by estimating a structural function for educational production. The determinants emphasized by these studies can be broadly grouped into three categories. More specifically, student-based characteristics such as age, gender, pre-primary education, school starting age, immigration background, peers’ mean test score, grade repetition in the past etc.

(Zimmer & Toma, 2000; Entorf & Minoiu, 2005; Sprietsma, 2010; Batyra, 2017; Bellibaş, 2016; Kasapoğlu, 2014; Ağırdağ et al., 2015); family-based characteristics such as parental working status, job type, home and cultural possessions, parental education, community location, etc. (Ammermueller et al., 2005; Woessmann, 2008; Peterson & Woessmann, 2007; Şirin, 2005; Yayan & Berberoğlu, 2004; Kasapoğlu, 2014; Ferreira & Gignoux, 2010; Blanchy & Şaşmaz, 2011; Kılıç et al., 2012; Özdemir, 2016; Batyra, 2017) and school based characteristics such as school location, educational expenditure per student, class size, shortage of materials, instruction time, teacher salaries, student-teacher ratio, teacher education, ICT usage at school, school type etc. (Hanushek & Kimko, 2000; Lee & Barro, 2001; Batyra, 2017; Dinçer & Uysal, 2010; Dinçer & Oral, 2013) are frequently emphasized in the estimation of the effects on student academic achievement at large scale student assessment tests. The data of test score achievement of students as well as variables of inputs to the education production function come from few international large scale student assessment tests such as well-known PISA, TIMMS, PIRLS etc. or nation-wide large scale student tests.

Apart from the above mentioned studies, a strand of literature has evolved to address predicting student academic performance and determine which elements are particularly useful in prediction of it. This strand of literature constitutes a subset of what has now been called as *Educational Data Mining* (EDM, thereafter) which mainly focuses on application of data mining, machine learning and statistical tools to extract useful information generated from educational settings (e.g., international large-scale student assessments, learning management systems, universities, administrative records etc.). The term educational data mining can be traced back to studies by Romero and Ventura (2007, 2010, 2013, 2020), and Baker and Yacef (2009). In those studies, authors point out the term educational data mining as a research area aimed at solving educational questions by means of analyzing educational dataset through data mining techniques.

Both strands of the literature namely Educational Production Function and Educational Data Mining are grounded in Walberg's (1981) theory of educational productivity which holds learning process of students as a production process, and uses various institutional, academic, demographic and economic factors in an analogy to the Cobb Douglas economic production equation. Moreover, educational productivity theory asserts complementarity of inputs, in other words it denies singularity of any factor that can affect learning achievement by itself instead achievement can be obtained only if all factors are combined. The way that these strands differ from each other depends on the purpose of the study. The main purpose is to determine the significance of each variables on student academic achievement by means of estimating a structural equation in Educational Production Function studies. On the other hand, in Educational Data Mining Studies, the main purpose is to determine the relevant variables in the prediction of student academic achievement and predicting the outcome accordingly. In fact, Educational Data Mining studies base their argument on the nature of the subject of the study. They argue that student learning and achievement can be influenced by vast amount of factors as the theory and empirical evidence suggests and since these factors are likely to interact with each other in complex and non-linear ways, machine learning methods can help researchers in selecting the top most important variables without imposing any prior functional-form assumption.

The literature on predictive elements and prediction of student academic performance is quite recent and still developing. Supervised learning techniques; more specifically classification and regression trees, support vector machine, variable selection methods, logistic regression, k-NN, and Naïve Bayes; are few examples of methods that are commonly employed in those studies. In a cross-country study, Chen et al. (2021) aimed to investigate the most important contextual characteristics of top performance[1] in science subject in PISA (Programme for International Student Assessment) 2015 cycle. The study which analyzes 58 countries, considered 141 variables of student, family and school levels from responses to PISA student and school questionnaires and by using support vector machine recursive feature elimination method it reports that there are 20 features that distinguishes top performers from non-top performers in science subject. Accordingly, the key aspects of top performers in PISA 2015 science subject are found to be as follows: They receive feedback related to their science learning, and their parents have high schooling level in terms of years together with mother and father with high

[1] There are 6 proficiency levels regarding scientific literacy in PISA 2015 cycle. PISA classifies students into those proficiency levels based on their performance at the test. Chen et al. (2021) defines top performance in science subject as performers of proficiency level 5 and proficiency level 6. Non-top performance therefore refers to below proficiency level 5.

occupational status. In addition to these features, teachers adapted their teaching according to students' needs, as well as directed most of the science classes, and provided both emotional and academic support for students' science learning during the classes. About disciplinary climate in science classes, disorder and classmate misbehavior sometimes arose. Furthermore, about each student is found to have a computer for educational purposes which has internet connection. In terms of teacher resources, total number of all teachers at school, total number of science teachers are reported to be high whereas student-teacher ratio is reported to be low among top performers of science subject in PISA 2015 cycle. Regarding student aspects, the study points out that top performers had attended early childhood education, had sometimes attended science-related activities, and they had confidence in solving science problems. The study by Hu et al. (2022) is an extension of Chen et al. (2021) in a way that it considers differentiating factors of high performers from low performers[2] in PISA 2015 science subject. By analyzing 127 student, family and school-level variables over 53 countries thorough support vector machine recursive feature elimination method the authors report a set of 30 key factors that distinguish high performers of science from that of low performers. The variables of perceived feedback related to science learning, index of occupational status of mother, possession of computers that have internet connection, teacher's adaptation of instruction, student related factors affecting school climate are also endorsed by Hu et al. (2022). In addition to those, expectations related to students' educational aspiration and occupational status, immigration status, gender, home-cultural and -wealth possessions, highest educational status of parents, epistemological beliefs and enjoyment of science, inquiry based science learning, teacher unfairness, quality assurance in school, parental involvement in school, internal school evaluation (feedback from students) and teacher collaboration are substantiated as contextual in affecting students' high and low performance in secondary science education.

Research on relational variables of students' academic achievement is not only conducted at cross-country level, but also at single country level (Gorostiaga & Rojo-Alvarez, 2016; Dong & Hu, 2019). In their study which analyzes mathematical performance of Spanish secondary school students at PISA 2009 round, Gorostiaga

[2] Hu et al. (2021) defines high performance in PISA 2015 science subject as science scores at proficiency level 6 and low performance in PISA 2015 science subject is defined as proficiency levels 1a and 1b.

and Rojo-Alvarez (2016) seek for classification of successful students[3] thorough machine learning algorithms of logistic regression, fisher discriminant analysis and support vector machine. It is stressed that three methods mostly agree on the features that are selected as relevant predictors of success at mathematics. It is found that boys are more likely to outperform girls in mathematics. Similarly, native students are reported as more likely to be classified as successful. Moreover, mother's occupational status (or job prestige) is stated as relevant to student's academic performance whereas the same does not apply to fathers. Furthermore; home-cultural possessions like books at home and works of art, ICT availability at home and ICT usage at school, students' reading engagement stimulation by teachers, regional and communital (i.e. village/town/city) variables and out-of-school lessons are noted as associated to successful performance of Spanish students. Related to empirical evidence from Singapore, the study by Dong and Hu (2019) examines reading literacy performance of secondary school students at PISA 2015 round. By employing support vector machine method, 15 features out of 49 considered variables are selected as influential on superior reading performance of Singaporean students. It is reported that student learning time in terms of minutes per week, student aptitude towards reading (e.g. interest in reading etc.), student attitude towards cooperation and status of grade repetition are influential at the student-level; index of economic, social and cultural status, cultural and home possessions, family wealth and ICT availability at home are influential at the family–level, and finally total enrollment of schools, instructional leadership of school principal, teacher participation, perceived feedback from teachers, teachers' adaptation of instruction and proportion of all teachers with ISCED[4] level 6 are found to be influential factors at the school-level.

Empirical evidence that is related to the factors leading students to academic success from studies using classification machine learning algorithm is provided for Turkish secondary school students, as well. Filiz and Öz (2019) provides evidence from TIMSS (Trends in International Mathematics and Science Study) 2015 science

[3] Dependent variable, which is defined as success in the mathematics subject of PISA 2009 round is dichotomous in the sense that successful students are those whose mathematics score is in the upper 25th percentile of the sample (Gorostiaga & Rojo-Alvarez, 2016).
[4] ISCED stands for international standard classification of education which is the official framework used to facilitate international comparisons of different education systems. Starting from level 0 there are 9 ISCED levels. ISCED level 6 refers to Bachelors degree or equivalent tertiary education level.

subject, and Uğuz et al. (2021) and Kasap et al. (2021) provide evidence from PISA 2018 science and reading subjects, respectively. For the purpose of specifying the appropriate classification method among Naïve Bayes, Logistic Regression, Support Vector Machine and Random Forest; and determining the features that are influential in student success; Filiz and Öz (2019) define the outcome variable as science success[5] of Turkish students and demonstrate that the most successful classifier algorithms are logistic regression and support vector machine. Besides, it is signified that out of 36 student-level features having shared computer tablet (i.e. not on somebody's own), having and the amount of extra science lessons, student's expected educational aspiration, availability of home educational resources, and student confidence in science subject are important in Turkish students' science achievement at TIMSS 2015 cycle. The single-country result from Türkiye about importance of student's perceived confidence in science subject and student's educational aspiration in science achievement in international student assessment tests is consistent with findings from cross-country evidence in the study by Hu et al. (2021). In terms of influence of extraneous lessons (or out of school lessons) on student performance at international student tests the results reached by Filiz and Öz (2019) for Türkiye confirms the results reached by Gorostiaga and Rojo-Alvarez (2016) for Spain.

A similar pattern of results are reached by the study of Kasap et al. (2021) where important variables predicting reading comprehension of secondary school students are attempted to be determined for 9 countries[6], including Türkiye. The study which employs logistic regression method to classify PISA 2018 reading literacy scores based on 34 independent variables from student and school questionnaires finds that home possessions, students' perception related to difficulty level of PISA assessment, highest occupational status of parents, parents' education level, student's expected occupational status and enjoyment in reading activities are important common predictors of students' performance in reading section of PISA for both Türkiye and other 8 countries. By employing Naïve Bayes, K-NN and Random Forest classification methods in Turkish students' science scores at PISA 2018 test,

[5] This is defined as binary in the sense that if the score is above the center point of 500, then the outcome is equal to 1, and 0 otherwise.

[6] These countries other than Türkiye are Indonesia, Colombia, Saudi Arabia, Serbia, Hungary, Slovenia, US and Finland.

Uğuz et al. (2021) confirms previous findings related to importance of time spent for science learning per week, the usage of ICT at school, and student's perception of ICT proficiency in science achievement of Turkish secondary school students. It should be noted that the dependent variables in studies by both Kasap et al. (2021) and Uğuz et al. (2021) are defined as average of 10 plausible values in reading subject area and science subject area of the PISA, respectively. However, it is explicitly noted in the PISA data analysis manual (OECD, 2009) that:

> Plausible values should never be averaged at the student level, *i.e.* by computing in the dataset the mean of the five plausible values at the student level and then computing the statistic of interest once using that average PV value. Doing so would be equivalent to an EAP (expected a posteriori) estimate, with a bias as described in the previous section. (p.100)

Therefore, the practice of averaging plausible values at student level, instead of using one of them or each one of them in the analysis may lead to flawed results as stated by the PISA data analysis manual.

In order to elucidate more the nonlinearity in the relationship between student academic achievement and various student, family and school level influencers, Decision Tree method (Classification and Regression Trees, CART thereafter) in terms of both classification and regression problems is employed in various studies. Employing Australian subset of PISA in year of 2012, Gabriel et al. (2018) interrogate the relationship between psychological dispositions together with a number of demographic variables and mathematics competency of Australian secondary school students through boosted regression trees. According to the results, the most influential input variable is students' self-efficacy (which is defined as "task- or situation- specific belief that an individual has that they can succeed"), and the second most important variable is ESCS (which refers to the PISA index of economic social and cultural status implying a composite measure of students' socioeconomic status). Indeed, out of 55 student level variables, 10 most influential variables on mathematics achievement of Australian secondary schoolers consist of psychological dispositions towards mathematics subject and a bunch of demographic variables. Moreover, with decision tree methodology, it is revealed that there exist a strong interaction between mathematics anxiety and mathematics self - efficacy and mathematics anxiety and mathematics self-concept. This refers to a very little effect of mathematics anxiety on mathematics performance of students who report very low self-efficacy and similarly, little effect of self-concept on the most anxious students. The model also elicited the nonlinear relationship such that mathematics self-efficacy has a greater positive effect on mathematics score in high ESCS students than in low ESCS students.

Masci et al. (2018) provide evidence related to impact of student and school -characteristics on mathematics literacy from a set of nine large developed countries; specifically Australia, Canada, France, Germany, Italy, Japan, Spain, UK and USA. By using PISA 2015 test scores and survey, boosted regression tree methodology is employed and following conclusions are reached: In almost all countries, most important variables are found as students' self-reported anxiety toward tests, socioeconomic status (as measured by ESCS index), self-reported motivation. More specifically, ESCS is reported to be the most important variable in mathematical literacy of students in Australia, France, Spain, UK and USA while students' self-reported anxiety is the most important variable in Canada, Germany and Italy. Furthermore, Japan is reported as the country where students' self-motivation is the most important variable. Besides, educational level of parents, educational resources at home, disciplinary climate and number of hours in mathematics lesson are other signified influencers. In another study, in terms of scientific literacy, the regression tree model picked out students' environmental awareness, presence of technological resources at home, home educational resources, science self-efficacy, epistemological beliefs about science, home possessions, family wealth, ESCS and total number of science teachers at school for 60 countries participating PISA 2015 (Puah, 2021).

A similar way of analysis -for USA and Canada- is carried by Liu and Whitford (2011) and Yu et al. (2012). By covering 23 home-based independent variables of student learning from US subset of PISA 2006 student survey, decision trees of US students' science competence implied that number of books at home -specifically less than or equal to 100 books- and large/small/one-to-one group out-of-school lessons with their teachers or other teachers are involved in profile of low student achievement, whereas more than 100 books at home and neither large nor small group or one-to-one out-of-school lessons with their teachers or other teachers and highest parental education, i.e. having or not graduate degree, are associated with the profile of high student achievement (Liu & Whitford, 2011). With the aim of accounting for important variables in the performance gap between American and Canadian secondary-schoolers at PISA 2006 science subject, Yu et al. (2012) employed CART and logistic regression in a machine learning framework and reached similar results. According to CART methodology, students' science enjoyment, number of books at home, frequent use of software for educational purposes and students' science interest play important role in superior PISA science achievement of Canadian second schoolers with respect to their American counterparts. The list of important variables is much longer based on the results implied by the logistic regression. In addition to aforementioned items, the number of TVs as well as the number of computers at home are reported to have important role in better performance of Canadian students at PISA 2006 science test. In another comparative study, Kılıç Depren (2018) accounts for science performance differential between Türkiye and the highest achieving country, Singapore. The study which employs multivariate adaptive regression splines (MARS) and CART on 53 different student related factors together with PISA 2015 science scores concludes that environmental optimism, environmental awareness, science learning time, home possessions, epistemological beliefs about science, economic social and cultural status (as measured by ESCS), inquiry based science teaching and learning practices, family wealth and test anxiety are the most influential for Turkish students based on both methods while for Singaporean students; mathematics learning time, teacher directed science instruction, school disciplinary climate, student self-efficacy, unfair teacher practices and ICT availability at school in addition to variables of science learning time, environmental optimism, environmental awareness, home possessions and ESCS are mostly pronounced.

Among the others, a cross-country study by Lee and Lee (2021) recognized likely importance of country level variables such as country's level of development and socioeconomic environment in student academic achievement in mathematics subject. In the study which covers 76 countries participating PISA 2018 round, light gradient boosting technique is employed in order to account for factors that are associated with student performance as well as explaining the differences in mathematics achievement between East Asian and non-East Asian students. Regarding the former objective, it is reported that 2 country level factors namely number of researchers in R&D, proportion of youth not in education, training or employment, 1 school level factor namely student behavior hindering learning and 12 student level factors namely mathematics learning time, grade repetition, ESCS, ICT resources at home, student's perception of PISA test's difficulty, student's expected occupational status, self-efficacy and self-awareness related to global issues etc. are the most informative when predicting student achievement. Related to the latter objective of the study, which is to identify the important features predicting elevated mathematics performance of East Asian students, it is reported that percentage of unemployed with basic education in addition to aforementioned country level factors; school type (i.e. private-independent), school size and class size in addition to previously found school level influencer; duration in early education and child care, ICT use outside school for leisure, discriminating school climate, and student's attitudes towards immigrants in addition to before-mentioned student level factors contribute most significantly to predicted outcome (Lee & Lee, 2021).

The current literature on the identification of factors that are influential in student academic performance at large scale student assessment tests abounds with examples from studies using decision trees in a single country setting. Martinez-Abad et al. (2020) carried out a two level-analysis in machine learning framework for Spanish secondary school students' achievement at all subject areas of PISA 2015. At the first level, high and low effective schools are identified by multilevel models which only include input variables, and selection is based on the analysis of residuals obtained in the school level. At the second level, factors associated with high and low effective schools are determined using decision trees method. Using a total of 59 variables as attributes lead the following conclusion that high effectiveness is mainly associated with students' high average attendance at academic extracurricular activities, availability and frequency of use of ICT in academic field, total hours per week of school lessons in reading, mathematics and science and lesser autonomy on school principal in the management of teaching staff of the school. A similar set of school-related attributes in relation to high performance are identified by the study for Tunisian secondary school students using decision trees. Random forest method indicates that the most important characteristics associated with higher performance are school size, competition, class size, parental pressure and proportion of girls (Rebai et al., 2020).

In the single country study framework, the outcomes reached by She et al. (2019), Martinez-Abad and Lopez (2017), Aksu and Güzeller (2016), and Kıray et al. (2015) differs from studies by Martinez-Abad et al. (2020) and Rebai et al.(2020) in that student-level characteristics are emphasized more than school-level ones in students' academic success at large scale student assessments. She et al. (2019) identifies epistemic beliefs about science, learning time, self-efficacy, students' interest in science and scientific inquiry as helping in differentiating Taiwanese secondary school students as high and low performers at PISA 2015 cycle. Martinez-Abad and Lopez (2017) draws on Mexican students' achievement at ENLACE test which is a national large scale student assessment in Mexico to assess variables related to academic performance. It is found that student related variables rather than school-related and social based are most indicative of academic performance of Mexican students. More specifically, variables indicating learning strategies, self-esteem, drug use, coexistence-violence, resources at home were found to be the most significant factors. Kıray et al. (2015) has attempted to account for the order of importance of variables which affect mathematics and science achievement of Turkish secondary school students. Using decision trees and clustering methods on TIMSS 1999, PISA 2003 and PISA 2006 test and questionnaire data, the findings show that following variables are the most important: Firstly, affective variables such as self-concept, interest, motivation, self-efficacy, anxiety and attitude, reading and problem solving skills are all influential on science and mathematics achievement. Secondly, under/achievement in any one of science or mathematics course affect each other. Third and lastly, the effect of achievement in mathematics on science achievement is much greater than that of science in accounting for mathematics. In the same vein, using PISA 2012 mathematics scores for Türkiye Aksu and Güzeller (2016) confirms that students' self-efficacy perception, attitude towards the course and studying discipline were found to be the most important affective characteristics in classification of successful and unsuccessful students.

The issue of determinants of student academic achievement at large scale student assessment tests is explored by studies of Puah (2021), and Yoo (2018) using variable selection methods in a machine learning context. For 60 countries which participated PISA 2015, Puah (2021) runs and compares prediction performances and the results implied by ridge regression, least absolute shrinkage Operator (LASSO), regression tree and traditional multilinear regression. Using a total of 66 independent variables of which had 24 student-related and 42 school-related variables, LASSO and elastic net are found to be the methods that produced the best predictive accuracy. Relatedly in all regression based machine learning methods, variables of home possessions, family wealth, students' epistemological beliefs about science often emerged as one of important variables in each model. Moreover, across all the variable selection methods school type (i.e. public school or private school) appears as associated with scientific literacy. Furthermore, LASSO and elastic net models indicate that students with better grades with respect to modal grade in their country were more likely to perform better. In a single country evidence, Yoo (2018) examines mathematical literacy of Korean students at TIMSS 2011 exam using elastic net variable selection model. Similar to often mentioned findings from previous studies in the literature, home possessions such as car ownership, internet connection and number of books, parental support and involvement, safe neighborhood, self-confidence and self-efficacy in mathematics are validated as important in student achievement (Yoo, 2018).

2.3. Data

The dataset of the present study comprises of the Programme for International Student Assessment (PISA, thereafter) test and surveys, which have been conducted by Organization for Economic Cooperation and Development (OECD) and national ministries of education of each country in every three years since 2000. More specifically, Turkish subset of PISA for the latest available year of 2018 will be examined so that it is extracted from the whole dataset, which is comprising of 79 countries in total, after merging available surveys based on the key variables: CNT and CNTSCHID as suggested by PISA Manual.

The main relationship that is going to be examined in this study is the one between student achievement and diverse set of educational achievement indicators for Turkish subsample of PISA for the latest available year which is 2018. For the output variable, the plausible values in each subject of literacy, for each student reported by PISA will be used. For the input variables, responses to main questionnaires (specifically student and school) from each same student and corresponding school principal will be employed. Unfortunately, teacher questionnaire is not completed by

Turkish teachers, so that it will not be utilized in this study. According to Türkiye Country Note of PISA 2018, there are total of 6890 students from 186 schools participated PISA 2018 cycle in Türkiye.

2.3.1. Sampling

Most PISA samples were designed as two-stage stratified samples. First stage sampled schools in which 15 year-old students may be enrolled. At least 150 schools were selected in each country, although the requirements for national analyses often demanded a larger sample. The second stage of the selection process sampled students within sampled schools. Once schools were selected, a list of each sampled school's 15 year old students was prepared. From this list, 42 students were then selected with equal probability (all 15-year-old students were selected if fewer than 42 were enrolled). The target number of students who were to be sampled in a school could deviate from 42 but could not fall below 20.

Two types of stratification are pursued in PISA samples as explicit stratification and implicit stratification. In explicit stratification, schools are grouped into strata that will be treated independently, as if they were separate schools sampling frames. Examples of explicit stratification can be states, regions etc. within a country. In implicit stratification, schools are sorted within each explicit stratum using a set of country-specific predetermined implicit stratification variables. Examples of implicit stratification can be type of school, urbanization, school size, minory composition etc. School type by percentile of performance, school gender composition, urbanization, funding and statistical regional units are stratified in sample selection in Türkiye.

2.3.2. Student Performance

The PISA has been designed to collect information about 15-year-old students[7] in participating countries. PISA collects and reports that information for each country in terms of participating students' achievement in subjects of reading, mathematics and scientific literacy. The aim of the exam is not only to assess what is learned by

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[7] Although, 15-year-olds are used as an abbreviation for the target population of PISA, it refers to students who are aged between 15 years and 3 months and 16 years and 2 months at the assessment time and who are enrolled in school and have completed 6 years of formal schooling at least.

students in school curriculum but also to measure how are students able to apply that knowledge in real world situations. For each student, PISA reports student performance in reading, mathematics and science subjects through plausible values instead of providing a single achievement score. Specifically, 10 plausible values are calculated for each student for every test in PISA 2018 cycle. It has been noted in PISA data analysis manual (OECD, 2009, p.89) that:

> The simplest way to describe plausible values is to say that plausible values are a representation of the range of abilities that a student might reasonably have. [...] Instead of directly estimating a student's ability θ , a probability distribution for a student's θ is estimated. That is, instead of obtaining a point estimate for θ, a range of possible values for a student's θ, with an associated probability for each of these values is estimated (Wu & Adams, 2002, as cited in OECD, 2009).

It is stated in the same manual that analysis has to be run separately for every plausible value and then the results should be aggregated. It is also stated in the same manual that using just one plausible value would also provide unbiased estimates. The biggest disadvantage of using only one plausible value is stated not to estimate imputation error that reflects the influence of test unreliability for the parameter estimation. However, for large datasets this error is negligible.

In PISA, students' performance results are classified into proficiency levels for each subject. There are 8 proficiency levels for reading subject, 6 proficiency levels for mathematics subject and 7 proficiency levels for science subject in PISA 2018 cycle. In all subjects, level 2 is considered to be the threshold at which students begin to demonstrate their capacity to use their reading/mathematics/science skills to acquire knowledge and solve problems. Students who performed at level 2 and below are considered to be low-performers. Similarly, students who performed at level 5 or more are considered to be top-performers. Table 2.1 briefly depict proficiency level cut-off score points as provided in PISA manual.

Table 2.1. Subject Proficiency Levels in PISA 2018

Proficiency Level	**Reading Lower Score Limit**	**Mathematics Lower Score Limit**	**Science Lower Score Limit**
6	698	669	708
5	626	607	633
4	553	545	559
3	480	482	484

Table 2.1.continued

Proficiency Level	Reading Lower Score Limit	Mathematics Lower Score Limit	Science Lower Score Limit
2	407	420	410
1a	335	358	335
1b	262		261
1c	189		

2.3.3. Survey

Together with student achievement in different literacy subjects, a number of questionnaires which were administrated to students, parents, teachers and school principals[8] to gather detailed information are collected in each PISA cycle. The background questionnaire answered by students elicited information about students themselves, their attitudes, dispositions and beliefs, motivation in relation to education, their home environments, their parents and their school and learning experiences. The background questionnaire completed by school principals sought information about aspects of schools, such as the quality of the schools' human and material resources, public and private management and funding, decision-making processes, staffing practices, the school's curricular emphasis and the extracurricular activities it offers etc. PISA reports the responses to those questionnaires together with students' performance results in each subject of assessment to depict a comprehensive picture of student, school and education system altogether. Among hundreds of variables that are surveyed by PISA student- and school principal questionnaires, a detailed list of variables and their descriptions have come into prominence in relevant predictors and prediction of student academic achievement literature.

2.4. Data Pre-Processing and Descriptive Analysis

In addition to assessing what students know and can do with their knowledge, PISA elicits a number of useful information related to student and school level variables for Turkish secondary school students. After considering the most prominent variables that emphasized by Educational Data Mining literature and the process of

[8] The background questionnaires completed by students and by school principals are the main questionnaires that were completed by all participating countries. However, the background questionnaires completed by teachers and by parents are stated as optional so that for some countries, including Türkiye, they are not complete.

data cleaning (i.e. handling of missing values), there are 3876 observations from 160 schools with a total of 71 student- and school-level variables that are going to be examined in the present study. Lists of student- and school - level variables and their explanations are provided in Table 2.2 and Table 2.3, respectively.

Table 2.2. Variable List at the Student Level Considered in the Study

Variable Code	Variable Description	Variable Type
ST001D01T	Student International Grade	Grade 9, 10, 11,12
ST004D01T	Student Gender	Nominal
ST013Q01TA	How many books are there in your home?	Ordinal
PROGN	Unique national study programme code	
HISEI	Index highest parental occupational status	Numerical, Index
LANGN	Language at home	3 digit code
PARED	Index highest parental education in years of schooling	Numerical (Min:3 Max:18)
IMMIG	Index Immigration status	Ordinal, 3 point Likert Scale: Native, Second Generation, First Generation
REPEAT	Grade Repetition	Nominal
BSMJ	Student's expected occupational status	Numerical, Index
MMINS	Mathematics learning time (minutes per week)	Numerical
SMINS	Science learning time (minutes per week)	Numerical
LMINS	Reading learning time (minutes per week)	Numerical
ESCS	Index of economic, social and cultural status	Numerical, Index
ICTHOME	ICT available at home	Numerical, Index
ICTSCH	ICT available at school	Numerical, Index
HOMEPOS	Home Possessions	Numerical, Index
CULTPOSS	Cultural Possessions	Numerical, Index
HEDRES	Home Educational Resources	Numerical, Index
WEALTH	Family Wealth	Numerical, Index
DISCLIMA	Disciplinary Climate in lessons	Numerical, Index
HOMESCH	Use of ICT outside of school (for school work activities)	Numerical, Index
ENTUSE	ICT use outside of school (leisure)	Numerical, Index
USESCH	Use of ICT at school in general	Numerical, Index

Table 2.2.continued

Variable Code	Variable Description	Variable Type
ICTCLASS	Subject-related ICT use during lessons	Numerical, Index
ICTOUTSIDE	Subject-related ICT use outside of lessons	Numerical, Index

Table 2.3. Variable List at the School Level Considered in the Study

Variable Code	Variable Description	Variable Type
SC001Q01TA	Which of the following definitions best describes the com munity in which your school is located?	Ordinal
PRIVATESCH	Private or Public	Nominal
SC016Q01TA	Percentage of total funding for school year from: Government	Percentage
SC016Q02TA	Percentage of total funding for school year from: Student fees or school charges paid by parents	Percentage
SC016Q03TA	Percentage of total funding for school year from: Benefact ors, donations etc.	Percentage
SC016Q04TA	Percentage of total funding for school year from: Other	Percentage
SC155Q01HA	School's capacity using digital devices: The number of digi tal devices connected to the Internet is sufficient	Ordinal, 4 point Likert Scale: Strongly Agree, Agree, Disagree, Strongly Disagree
SC155Q02HA	School's capacity using digital devices: The school's Intern et bandwidth or speed is sufficient	Ordinal, 4 point Likert Scale: Strongly Agree, Agree, Disagree, Strongly Disagree
SC155Q03HA	School's capacity using digital devices: The number of digi tal devices for instruction is sufficient	Ordinal, 4 point Likert Scale: Strongly Agree, Agree, Disagree, Strongly Disagree
SC155Q04HA	School's capacity using digital devices: Digital devices are sufficiently powerful in terms of computing capacity	Ordinal, 4 point Likert Scale: Strongly Agree, Agree, Disagree, Strongly Disagree
SC155Q05HA	School's capacity using digital devices: The availability of adequate software is sufficient	Ordinal, 4 point Likert Scale: Strongly Agree, Agree, Disagree, Strongly Disagree

Table 2.3.continued

Variable Code	Variable Description	Variable Type
SC155Q06HA	School's capacity using digital devices: Teachers have the skills to integrate digital devices in instruction	Ordinal, 4 point Likert Scale: Strongly Agree, Agree, Disagree, Strongly Disagree
SC155Q07HA	School's capacity using digital devices: Teachers have suff icient time to prepare lessons integrating digital devices	Ordinal, 4 point Likert Scale: Strongly Agree, Agree, Disagree, Strongly Disagree
SC155Q08HA	School's capacity using digital devices: Effective professio nal resources for teachers to learn how to use digital device	Ordinal, 4 point Likert Scale: Strongly Agree, Agree, Disagree, Strongly Disagree
SC155Q09HA	School's capacity using digital devices: An effective online learning support platform is available	Ordinal, 4 point Likert Scale: Strongly Agree, Agree, Disagree, Strongly Disagree
SC155Q10HA	School's capacity using digital devices: Teachers are provi ded with incentives to integrate digital devices	Ordinal, 4 point Likert Scale: Strongly Agree, Agree, Disagree, Strongly Disagree
SC155Q11HA	School's capacity using digital devices: The school has suf ficient qualified technical assistant staff	Ordinal, 4 point Likert Scale: Strongly Agree, Agree, Disagree, Strongly Disagree
SC011Q01TA	Which of the following statements best describes the schooling available to students in your location?	Ordinal, 3 point Likert Scale: More than one, One, None
SC012Q01TA	Student admission to school: Student's record of academic performance (including placement tests)	Ordinal, 3 point Likert Scale: Never, Sometimes, Always
SC042Q01TA	School's policy for 15-year olds: Students are grouped by ability into different classes.	Ordinal, 3 point Likert Scale: All subjects, Some subjects, Not for any subjects

Table 2.3.continued

Variable Name	Variable Description	Variable Type
SC042Q02TA	School's policy for 15-year-olds: Students are grouped by ability within their classes.	Ordinal, 3 point Likert Scale: All subjects, Some subjects, Not for any subjects
STUBEHA	Student behavior hindering learning	Numerical, Index
TEACHBEHA	Teacher behavior hindering learning	Numerical, Index
EDUSHORT	Shortage of educational material	Numerical, Index
STAFFSHORT	Shortage of educational staff	Numerical, Index
CREACTIV	Creative extra-curricular activities	Numerical, Index
PROATCE	Index proportion of all teachers fully certified	Numerical, Index
PROAT6	Index proportion of all teachers ISCED LEVEL 6	Numerical, Index
PROAT5AB	Index proportion of all teachers ISCED LEVEL 5A Bachelor	Numerical, Index
PROAT5AM	Index proportion of all teachers ISCED LEVEL 5A Master	Numerical, Index
SCHSIZE	School Size (Sum of boys and girls)	Numerical
SC002Q01TA	What was the total school enrolment (number of students)? Number of boys	Numerical
SC002Q02TA	What was the total school enrolment (number of students)? Number of girls	Numerical
TOTAT	Total number of all teachers at school	Numerical
SC025Q01NA	During the last three months, what percentage of teaching staff attended a programme of professional development?	Percentage
CLSIZE	Class size	Ordinal
SC164Q01HA	In the last full academic year, what proportion of students in final grade left school without a certificate?	Percentage
SC152Q01HA	Does your school offer additional test language lessons dur ing the usual school hours?	Nominal: Yes, No
SC052Q01NA	For 15year old students, school provides study help: Room (s) where the students can do their homework	Nominal: Yes, No
SC052Q02NA	For 15year old students, school provides study help: Staff help with homework	Nominal: Yes, No
SC052Q03HA	For 15-year old students, school provides study help: Peer-to-peer tutoring	Nominal: Yes, No

Table 2.3.continued

Variable Name	Variable Description	Variable Type
SCHLTYPE	School Ownership	Nominal, Public, Private, Private-Government dependent
STRATIO	Student-Teacher Ratio	Percentage
RATCMP1	Number of available computers per student at modal grade	Numerical
HIGHSCHOOL TYPE	Type of Highschool	Categorical: Anatolian, Imam-Preacher, Vocational-Technical, Science, Social Science, Sports-Fine Arts, Multi-Programme, Lower Secondary

Table 2.4 briefly presents the descriptive statistics of first plausible values of each subject from Turkish subsample of PISA 2018. On average, Turkish students are more successful in science and reading subject areas with respect to mathematics subject in PISA 2018. In terms of variability, such an inequality is reversed. In other words, the variability of test scores of mathematics subject area is the greatest than that of science and reading subject areas. As consistent with the variability implications from standard deviation statistic, the difference between the maximum and the minimum values in test scores is the greatest for the mathematics subject. It is the second greatest for the reading subject. Finally, as the second quartile (median) reflect the 50 - percentile statistic which shows the value below which the corresponding per cent of the observations may be found, is the lowest in mathematics subject area.

Table 2.4. Descriptive Statistics of Outcome Variables in Each Subject for Turkish subsample of PISA 2018

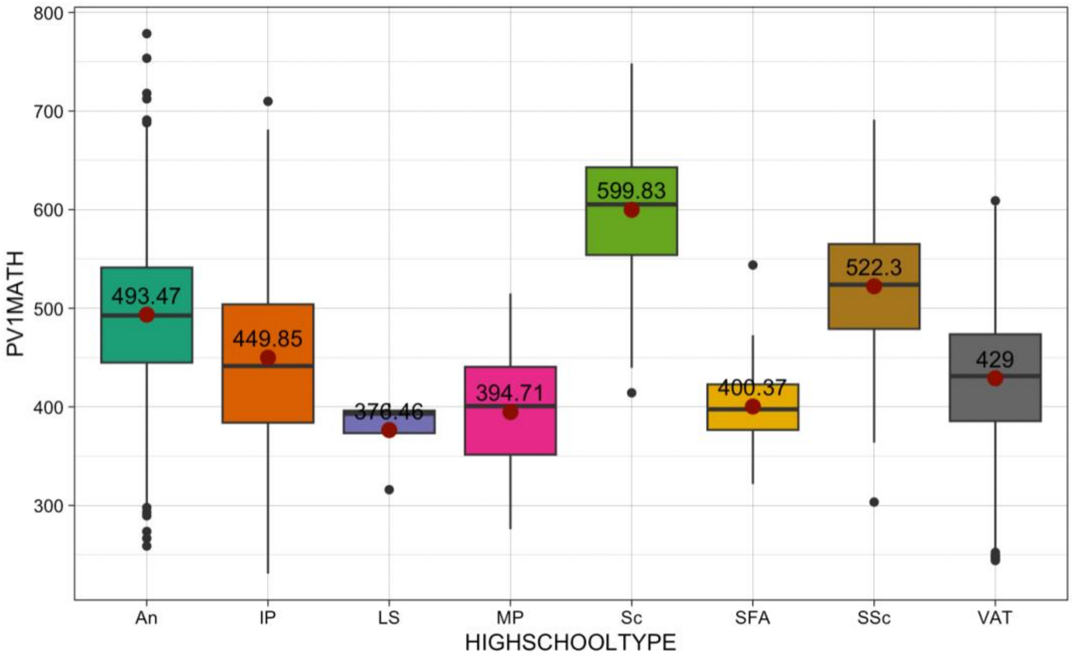
	PV1MATH	PV1SCIENCE	PV1READING
Minimum	230.881	243.397	241.229
Maximum	778.445	725.275	748.371

Table 2.4.continued

	PV1MATH	PV1SCIENCE	PV1READING
Range	547.564	481.878	507.142
Standard Deviation	83.379	78.995	82.672
Mean	470.319	484.097	483.773
Median	466.5055	482.365	482.853
Coefficient of Variation	0.1773	0.1632	0.1709

Figure 2.1 displays the box plots of students' performance at mathematics subject in PISA 2018 test by school programme types at which they are enrolled. It can be deduced that for the mathematics subject, Turkish students from Science High Schools are, on average, score greater than the rest of school programme types. In addition, students from Science High Schools, on average, score greater than the country average which is approximately equal to 470. Social Sciences High Schools and Anatolian High Schools are the next most successful school types in the PISA 2018 exam. Similar to students from Science High Schools, students enrolled at these schools , on average, tend to score greater than the country average. Considering the fact that students are placed to each school according to their previous achievement at a highly selective external exam which is conducted nation-wide in Türkiye, it is no surprise that students from these schools are the most successful in terms of knowledge and application of it. The high schools of Anatolian Imam and Preacher, Anatolian Sports and Fine Arts, Multi Programme Anatolian and Vocational and Technical, and Lower Secondary Schools have means slightly over than 400 points and this score is less than the country average of 470. Finally, together with proficiency levels calculated by PISA (as given by Table 2.1).

Figure 2.1. Plausible Values of 2018 PISA Mathematics Subject by School Programme Types

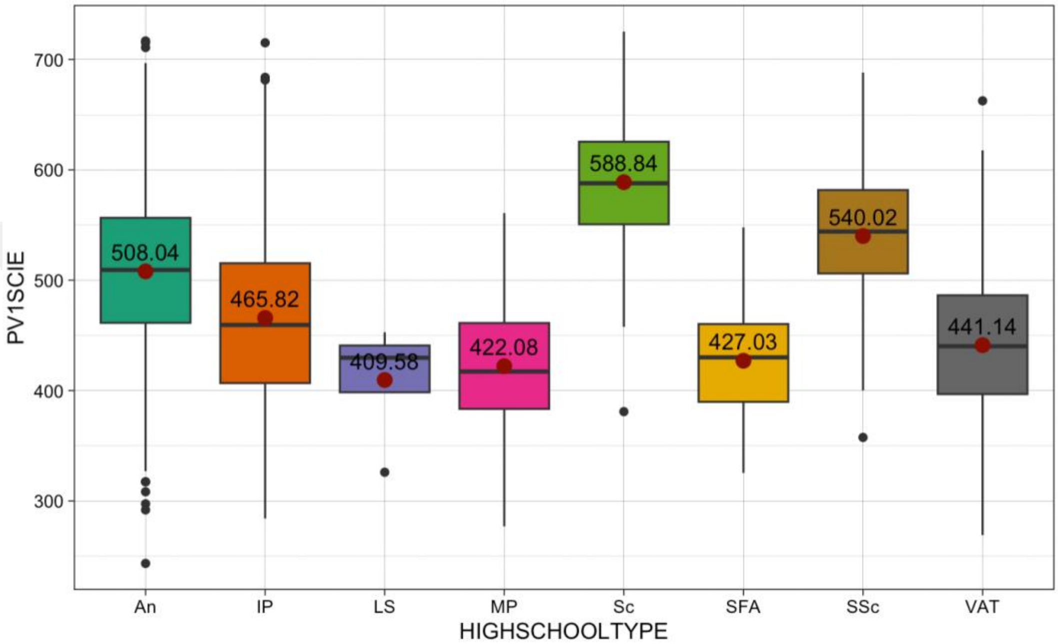


Note: An: Anatolian Highschool, IP: Imam-Preacher Anatolian Highschool, LS: Lower Secondary School, MP: Multi Programme Highschool, Sc: Science Highschool, SFA: Sports and Fine Arts Highschool, SSc: Social Science Highschool, VAT: Vocational and Technical Highschool.

Figure 2.1 implies that in terms of mathematical literacy, on average, Turkish secondary schoolers except those from high schools of Anatolian Sports and Fine Arts and Multi Programme Anatolian and Lower Secondary Schools are middle performers such that the average scores attained by those students are greater than 420 points which corresponds to level 2 proficiency according to PISA and less than 607 points which corresponds to level 5 proficiency according to PISA.

A similar pattern in achievement of students by their school programme types can be observed for the science subject in PISA 2018 test, as well. According to Figure 2.2 for the science subject, Turkish students from Science High Schools are, on average, score greater than the rest of school programme types. In addition, students from Science High Schools, on average, score greater than the country average which is approximately equal to 485. Social Sciences High Schools and Anatolian High Schools are the next most successful school types in the PISA 2018 exam. Similar to students from Science High Schools, students enrolled at these schools , on average, tend to score greater than the country average. Finally, together with proficiency levels calculated by PISA (as given by Table 2.1) Figure 2.2 implies that in terms of scientific literacy, on average, Turkish secondary schoolers except those from Lower Secondary Schools are middle performers such that the average scores attained by those students are greater than 410 points which corresponds to level 2 proficiency according to PISA and less than 633 points which corresponds to level 5 proficiency according to PISA.

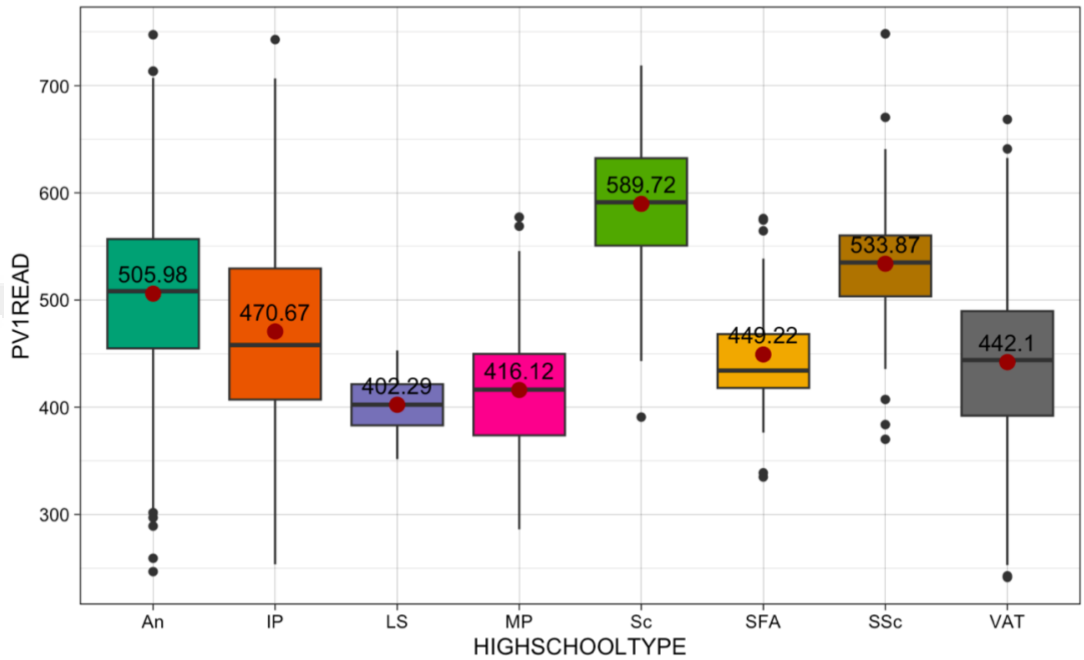
Figure 2.2. Plausible Values of 2018 PISA Science Subject by School Programme Types



Note: An: Anatolian Highschool, IP: Imam-Preacher Anatolian Highschool, LS: Lower Secondary School, MP: Multi Programme Highschool, Sc: Science Highschool, SFA: Sports and Fine Arts Highschool, SSc: Social Science Highschool, VAT: Vocational and Technical Highschool.

Previous conclusions related to mathematics and science subject literacy of Turkish students at PISA 2018 also holds for reading subject area based on Figure 2.3. Students from Science High Schools are, on average, score greater than the rest of school programme types. In addition, students from Science High Schools, on average, score greater than the country average which is approximately equal to 484. Social Sciences High Schools, Anatolian High Schools and Anatolian Imam and Preacher High Schools are the next most successful school types in the reading subject of PISA 2018 exam. Similar to students from Science High Schools, students enrolled at these schools , on average, tend to score greater than the country average. Finally, together with proficiency levels calculated by PISA (as given by Table 2.1) Figure 2.3 implies that in terms of reading literacy, on average, Turkish secondary schoolers are middle performers such that the average scores attained by those students are greater than 410 points which corresponds to level 2 proficiency according to PISA and less than 633 points which corresponds to level 5 proficiency according to PISA.

Figure 2.3. Plausible Values of 2018 PISA Reading Subject by School Programme Types

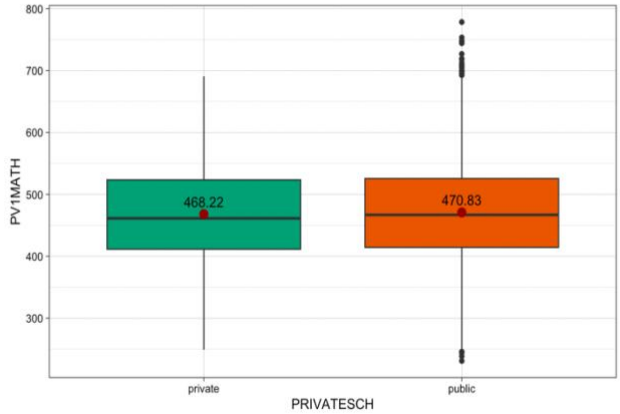


Note: An: Anatolian Highschool, IP: Imam-Preacher Anatolian Highschool, LS: Lower Secondary School, MP: Multi Programme Highschool, Sc: Science Highschool, SFA: Sports and Fine Arts Highschool, SSc: Social Science Highschool, VAT: Vocational and Technical Highschool.

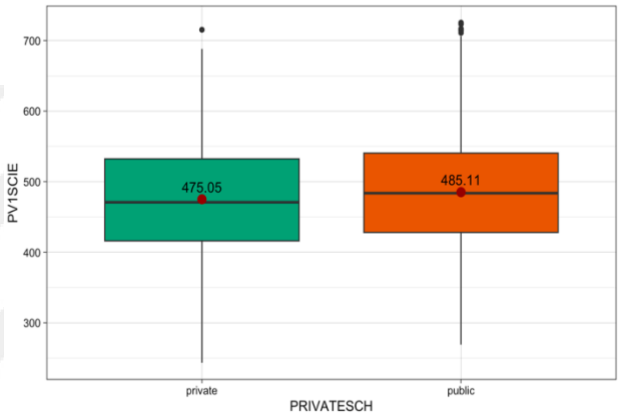
Plausible values from each subject area in 2018 PISA are examined according to school types in terms of public and private. Figure 2.4 reveals that, on average, public schools are slightly more successful in each area of subject. In terms of variability, scores are more or less the same dispersed around 475 points. In addition, outliers are quite more present in public schools with respect to private schools. These conclusions are valid across all subject areas for Turkish subset in PISA 2018.

Figure 2.4. Plausible Values of 2018 PISA Scoresby School Types

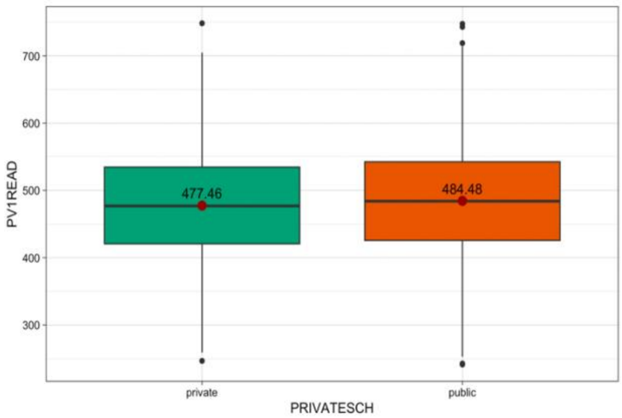
Mathematics Subject



Science Subject



Reading Subject



Plausible values of mathematics, science and reading subjects based on school programme types are depicted in Figure 2.5. It is clear from Figure 2.5 that students from high schools of general secondary education are on average more successful in all subject areas than students from high schools of vocational and technical education.

Figure 2.5. Plausible Values of 2018 PISA Scores by School Programme Types

Mathematics Subject

Science Subject

Reading Subject

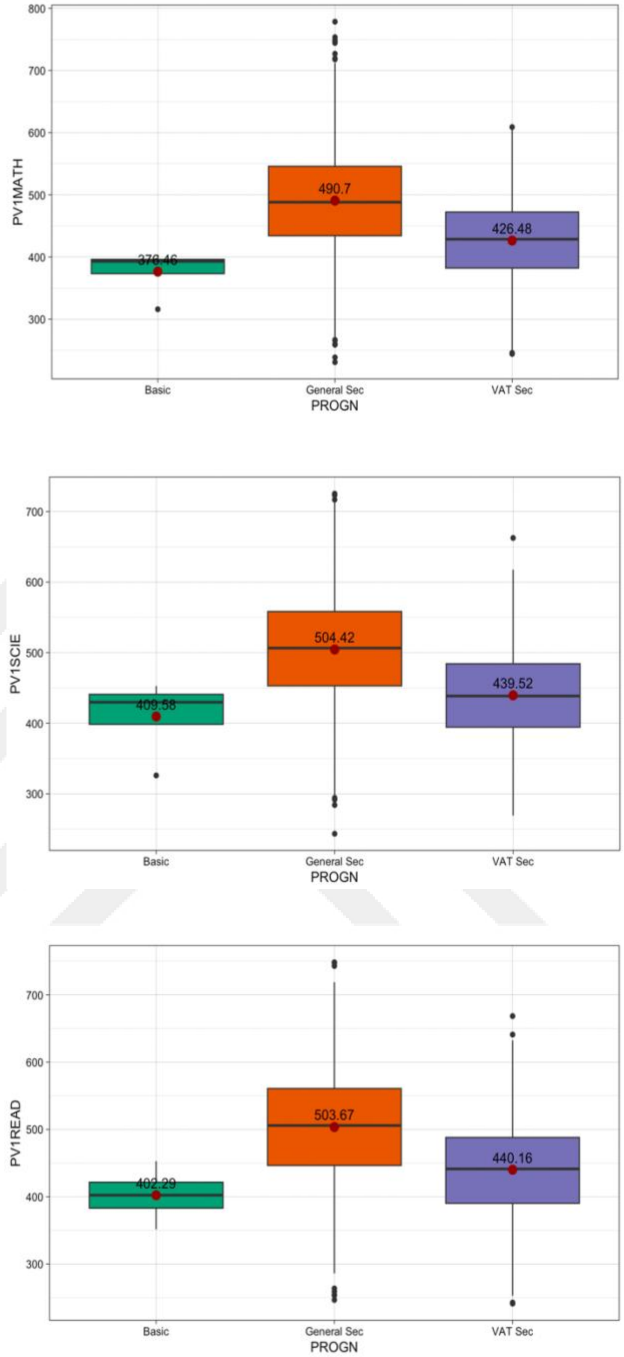


Figure 2.6. Cross Correlations between Plausible Values of Mathematics

	PV1MATH	PV2MATH	PV3MATH	PV4MATH	PV5MATH	PV6MATH	PV7MATH	PV8MATH	PV9MATH	PV10MATH
PV1MATH	1.00	0.85	0.85	0.85	0.85	0.84	0.85	0.85	0.85	0.85
PV2MATH	0.85	1.00	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85
PV3MATH	0.85	0.85	1.00	0.85	0.85	0.85	0.85	0.85	0.85	0.85
PV4MATH	0.85	0.85	0.85	1.00	0.84	0.84	0.84	0.85	0.85	0.85
PV5MATH	0.85	0.85	0.85	0.84	1.00	0.85	0.85	0.85	0.85	0.85
PV6MATH	0.84	0.85	0.85	0.84	0.85	1.00	0.84	0.85	0.85	0.85
PV7MATH	0.85	0.85	0.85	0.84	0.85	0.84	1.00	0.85	0.85	0.85
PV8MATH	0.85	0.85	0.85	0.85	0.85	0.85	0.85	1.00	0.85	0.85
PV9MATH	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	1.00	0.85
PV10MATH	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	1.00

Figure 2.7. Cross Correlations between Plausible Values of Science

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE	PV6SCIE	PV7SCIE	PV8SCIE	PV9SCIE	PV10SCIE
PV1SCIE	1.00	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
PV2SCIE	0.88	1.00	0.88	0.87	0.88	0.88	0.88	0.88	0.88	0.87
PV3SCIE	0.88	0.88	1.00	0.88	0.88	0.88	0.88	0.88	0.88	0.88
PV4SCIE	0.88	0.87	0.88	1.00	0.87	0.88	0.88	0.88	0.88	0.87
PV5SCIE	0.88	0.88	0.88	0.87	1.00	0.88	0.88	0.88	0.88	0.88
PV6SCIE	0.88	0.88	0.88	0.88	0.88	1.00	0.88	0.88	0.88	0.88
PV7SCIE	0.88	0.88	0.88	0.88	0.88	0.88	1.00	0.88	0.88	0.88
PV8SCIE	0.88	0.88	0.88	0.88	0.88	0.88	0.88	1.00	0.88	0.88
PV9SCIE	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	1.00	0.88
PV10SCIE	0.88	0.87	0.88	0.87	0.88	0.88	0.88	0.88	0.88	1.00

Figure 2.8. Cross Correlations between Plausible Values of Reading

	PV1READ	PV2READ	PV3READ	PV4READ	PV5READ	PV6READ	PV7READ	PV8READ	PV9READ	PV10READ
PV1READ	1.00	0.92	0.92	0.92	0.92	0.93	0.92	0.92	0.92	0.92
PV2READ	0.92	1.00	0.92	0.92	0.92	0.93	0.92	0.92	0.92	0.92
PV3READ	0.92	0.92	1.00	0.92	0.92	0.92	0.92	0.92	0.92	0.92
PV4READ	0.92	0.92	0.92	1.00	0.92	0.92	0.92	0.92	0.92	0.92
PV5READ	0.92	0.92	0.92	0.92	1.00	0.92	0.92	0.92	0.92	0.92
PV6READ	0.93	0.93	0.92	0.92	0.92	1.00	0.92	0.92	0.92	0.92
PV7READ	0.92	0.92	0.92	0.92	0.92	0.92	1.00	0.92	0.92	0.92
PV8READ	0.92	0.92	0.92	0.92	0.92	0.92	0.92	1.00	0.92	0.92
PV9READ	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	1.00	0.93
PV10READ	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.93	1.00

Figure 2.6, Figure 2.7 and Figure 2.8 depict the correlation coefficients within each subject area for Turkish subsample of PISA 2018. It is obvious that all the plausible values of each subject area are highly and positively correlated with each other. This is slightly more pronounced for reading subject area rather than for mathematics and science subjects. Based on the conclusion that is drown out of cross correlations within each subject area, and the subject score usage suggestion from PISA, the first plausible values for each subject are going to be the outcome variable of this study.

Table 2.5 summarizes the descriptive statistics of feature variables of main interest as well as of the outcome variables. More specifically, Table 2.4 presents summary statistics of economic, social and cultural status index (ESCS), highest parental occupational status (HISEI), highest parental education in years (PARED), family wealth index (WEALTH), student-teacher ratio (STRATIO), mathematics subject study time in minutes per week (MMINS), science subject study time in minutes per week (SMINS) and reading subject study time in minutes per week (RMINS) for Turkish subsample of PISA 2018. According to Table 2.5, on average parental highest educational years of schooling index is 11.073. In terms of variability, the difference between the minimum and maximum years of parental schooling index is equal to 13. Turkish students, on average study mathematics subject more than the other two subjects. The difference between the maximum and the minimum amount of time in terms of minutes per week is equal to 1040, 1710 and 1600 minutes per week for mathematics, science and reading subjects, respectively. Standard deviation approves that the most variability exists for science subject. The student-teacher ratio among Turkish secondary schools sample is, on average, equal to 13.73 students per teacher. This ratio is equal to minimum 2.34 students per teacher whereas it is, on maximum, equal to 40.759 students per teacher. Consequently, the spread between the two is quite large: 38.419 students per teacher. Finally, the median student-teacher ratio equals to 14.019 students per teacher.

Table 2.5. Descriptive Statistics of Feature Variables for Turkish subsample of PISA 2018

	ESCS	HISEI	PARED	WEALTH	STRATIO	MMINS	SMINS	RMINS
Min	-4.75	11.56	3	-4.94	2.34	40	0	0
Max	2.76	88.96	16	3.523	40.76	1080	1710	1600

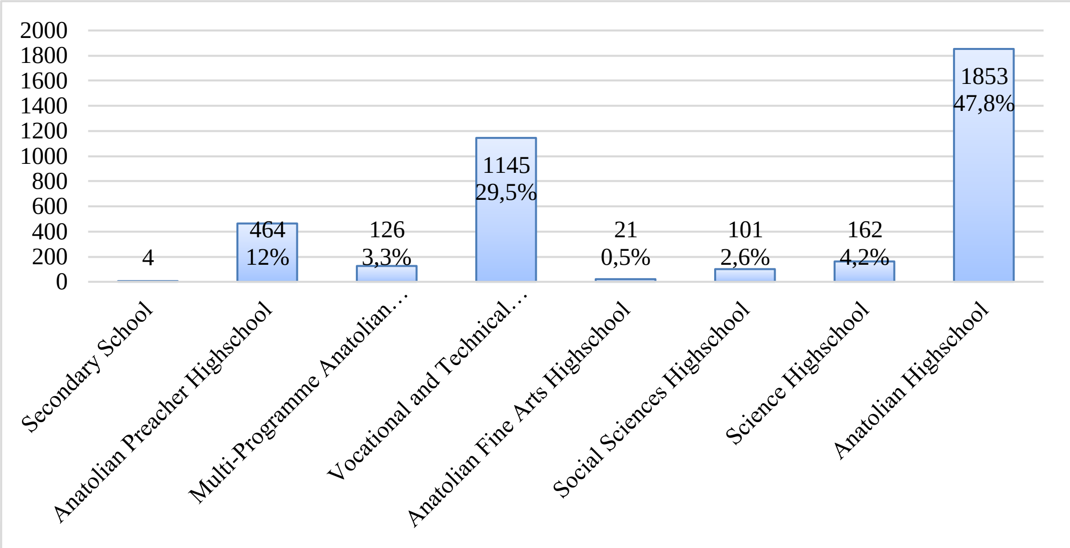
Table 2.5.continued

	ESCS	HISEI	PARED	WEALTH	STRATIO	MMINS	SMINS	RMINS
Range	7.51	77.4	13	8.467	38.42	1040	1710	1600
Standard Deviation	1.176	23.251	4.266	0.907	3.459	81.499	119.597	75.719
Mean	-1.047	39.68	11.073	-1.260	13.73	233.39	208.54	207.51
Median	-1.18	30.34	12	-1.243	14.019	240	240	200
Coefficient of Variation	0.89	0.586	0.3853	0.7198	0.2519	0.349	0.574	0.3649

The index of highest parental occupational status (HISEI) is derived from students' responses to open-ended questions related to father's and mother's occupations. Higher HISEI indicates higher levels of occupational status (OECD, 2019). Based on the statistics in Table 2.5, mean of the index of HISEI is equal to 39.679. The minimum and maximum values take 11.56 and 88.96 respectively. Family wealth (WEALTH) is another index derived from students' responses to a range of questions related to home possession variables as well as home educational resources including a room of somebody's own; connection to Internet; possession of works of art, number of books at home, televisions, cars, air conditioner; affording a holiday etc. According to Table 2.5, on average this index is equal to -1.26. The minimum and maximum values take -4.944 and 3.523 respectively.

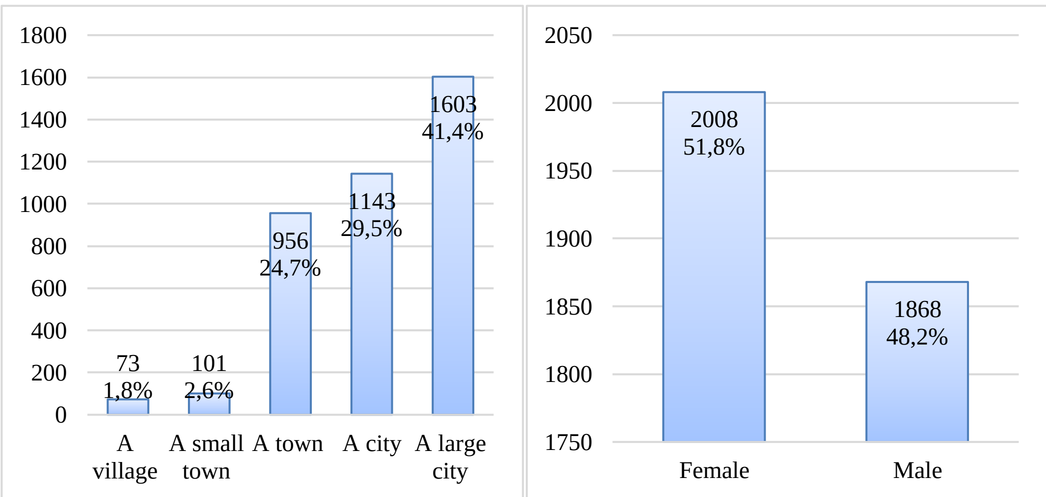
Figure 2.9 displays the proportion of each school type in Turkish subsample of PISA 2018. There are eight programme types at which a secondary school pupil can be enrolled in Türkiye. It is seen from Figure 2.10 that 48% of the sample is enrolled at Anatolian High schools. Enrollment to Vocational and Technical High schools is the second highest, and so on. It is worth noting that this scheme is quite similar to enrollment at Türkiye-wide.

Figure 2.9. Proportion of Programme Types among High Schools and Number of Enrollments



Proportions of variables related to school community location, gender, school type in terms of public or private and language spoken at home are depicted in Figure 2.10. Accordingly, students of Turkish sample from PISA 2018 mostly reside in a large city, and then in a city and in a town (Panel (a) in Figure 2.10) The gender composition of the sample is more or less balanced (Panel (b) in Figure 2.10). The most of the schools drawn from the population are public schools (Panel (c) in Figure 2.10). Finally, Turkish is the most general language spoken at home (Panel (d) in Figure 2.10).

Figure 2.10. Proportion of: School Community Location, Gender, School type in terms of public or private, Language spoken at home



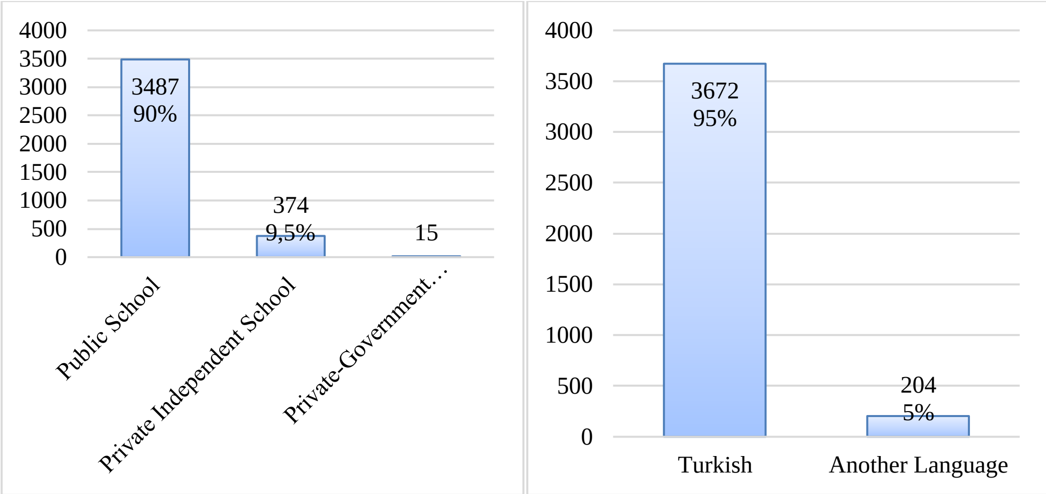


Figure 2.11. Proportion and Number of Enrollments by Grades in the Sample

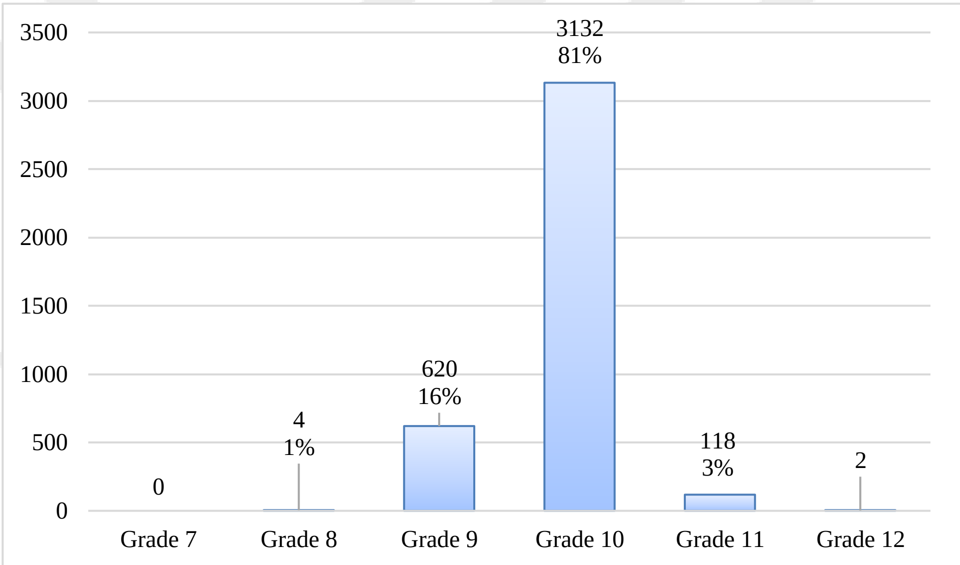
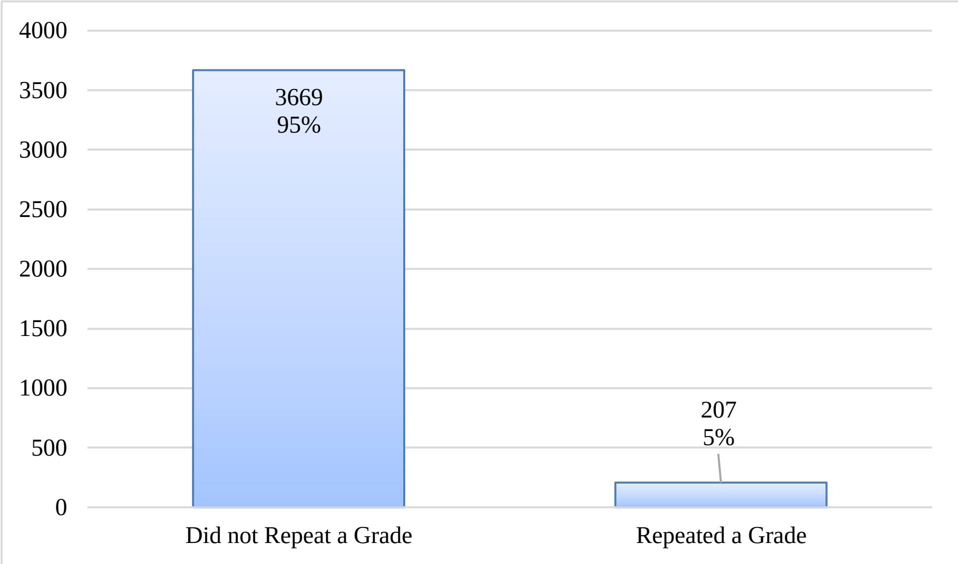


Figure 2.11 presents the proportion and number of grades that sampled students are in. Accordingly, most of the students are enrolled at grade 10 and then grade 9 and grade 11, so on.

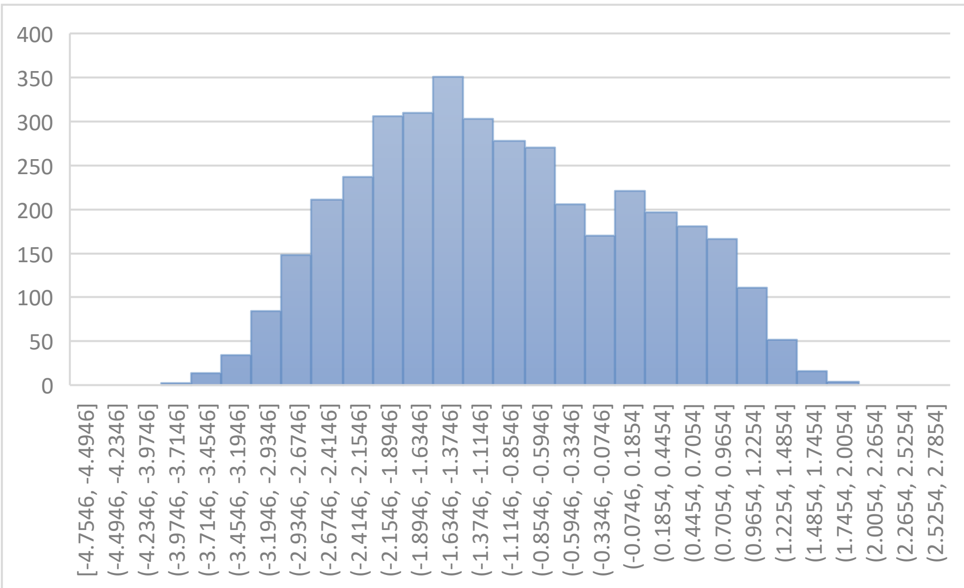
Figure 2.12 presents the proportion and number of grade repetition among the sampled students. Accordingly, 95% of the students in the sample did not repeat a grade in the past.

Figure 2.12. Proportion and Number of Grade Repetition in the Sample



The index of economic, social and cultural status (ESCS) is calculated by PISA using parents' education, parents' occupation and the index of home possessions which can be considered as proxies of material wealth or cultural capital. ESCS has traditionally been built as a weighted average of three indices: parental educational attainment (in years), parental occupational status on the "International Socio-Economic Index" (ISEI) scale and a measure of possessions at home.

Figure 2.13. Histogram of ESCS Index



According to Figure 2.13, there are two peaks indicating that the most occurring values are in between -1.63 and -1.25 and in between 0 and 1.25. The distribution of the observations in the sample is more or less symmetric and there exist outliers in the sample.

2.5. Methodology

As introduced earlier, the main purpose of this paper is to track down relevant features related to the prediction of success of Turkish secondary school students in order to better fit education policies proposed by policy-makers. In this manner, predictive performances of several models such that Multiple Linear Regression, Regularization (Shrinkage) Regressions and Decision Trees in Turkish secondary school students' success are compared and contrasted. In that fashion, the most influential features that come forward in predicting Turkish students' success are attempted to be determined with machine learning tools. In the following, each of these methods will be briefly introduced.

2.5.1. Multiple Linear Regression Model

Multiple Linear Regression is an extension of Simple Linear Regression which takes the form:

$$y = f(x) + \varepsilon, \tag{2.1}$$

where y denotes outcome variable, x denotes predictor (feature, attribute) variable of y, $f(x)$ is an unknown function and ε is a zero-mean random error term. If f is to be represented by linear function, then the relationship can be written as:

$$y = \beta_0 + \beta_1 x + \varepsilon \tag{2.2}$$

which is named as population regression function. In a multiple linear regression, there are p distinct predictors which are linearly related to the outcome, and the relationship takes the form:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p + \varepsilon \tag{2.3}$$

where $\beta_0, \beta_1 \ldots \beta_p$ denote unknown regression coefficients to be estimated using ordinary least squares method. Given estimates of regression coefficients as $\hat{\beta}_0, \hat{\beta}_1, \ldots, \hat{\beta}_p$, predictions can be made using the formula:

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \cdots + \hat{\beta}_p x_p \quad \textbf{(2.4)}$$

which is named as sample regression function. Regression coefficients are chosen to minimize the sum of squared residuals:

$$RSS = \sum_{i=1}^{n} \hat{\varepsilon}_i^2 \quad \textbf{(2.5)}$$

$$= \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

$$= \sum_{i=1}^{n} (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{i1} - \hat{\beta}_2 x_{i2} - \cdots - \hat{\beta}_p x_{ip})^2 \quad \textbf{(2.6)}$$

where n denotes the number of observations. Ordinary Least Squares estimates of regression coefficients are the best linear unbiased estimators of true parameters under the assumptions of exogeneity, homoscedasticity, linearity in parameters, no autocorrelation and zero error variance.

2.5.2. Variable Selection (Regularization) Models

Traditional methods are likely to suffer from the problem of overfitting which can be defined as the situation where the established model performs well for the data, which is used to build the model, whereas it poorly performs on the unseen data. This may stem from the nature of modelling a relationship between variables in a given sample which is drawn from a population and this process may have sampling error which is sample-specific and isn't shared with other samples drawn from the same population.

Another problem arises with traditional methods when there exist a large number of predictors, *p*, together with a large number of observations, *n*. It may be the case that some of predictors in a multiple regression model are not in fact related to the outcome variable. Inclusion of such irrelevant variables yields extra complexity on the resulting model. As the model becomes more complex, the poorer its prediction performance, hence suffers from overfitting. As a solution, some of the variables can be removed from the model by setting their coefficient estimates equal to 0 or bringing those coefficients closer to 0. In the following, the most common variable selection methods (regularization, shrinkage methods) are briefly described.

2.5.2.1. Ridge Regression

Ridge regression is very similar to least squares except that coefficients are estimated by minimizing:

$$RSS = \sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_{ij})^2 + \lambda_2 \sum_{j=1}^{p}\beta_j^2 = RSS + \lambda_2 \sum_{j=1}^{p}\beta_j^2 \qquad \textbf{(2.7)}$$

where $\lambda_2 \geq 0$ is the tuning parameter of the model. The first term in the expression above is the OLS part and the second term is the penalty function, which is also called as L_2 penalty. When $\lambda_2 = 0$, the penalty term has no effect hence ridge regression produces estimates will tend toward zero. Ridge regression produces different set of coefficient estimates for each value of λ_2.

2.5.2.2. Least Absolute Shrinkage Operator (LASSO)

In LASSO regression coefficients are estimated by minimizing the following:

$$RSS = \sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_{ij})^2 + \lambda_1 \sum_{j=1}^{p}|\beta_j| \qquad \textbf{(2.8)}$$

LASSO equation differs from the ridge regression equation in the penalty function named as L_1 penalty. Similar to the ridge regression, λ_1 controls the amount of regularization. As λ_1 gets larger, LASSO coefficients shrink more and smaller values of the former makes the above expression more similar to OLS regression. However, L_1 penalty which is the second term in the expression, has an effect to force some of the coefficient estimates to be equal to zero as the tuning parameter is large enough. Therefore, LASSO performs variable selection while the ridge does not.

2.5.2.3. Elastic Net

Elastic Net equation applies both L_1 and L_2 penalties bridging between LASSO and ridge regressions as:

$$RSS = \sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_{ij})^2 + \lambda\sum_{j=1}^{p}(\alpha|\beta_j| + (1-\alpha)\beta_j^2) \tag{2.9}$$

There are two tuning parameters in elastic net regression as α which bridges between ridge and LASSO and λ which regularizes the regression as explained before. The value of α ranges between zero and one determines whether the model is closer to LASSO or ridge regression.

2.5.3. Decision Trees (Ensemble Methods)

If the relationship between the outcome and features is well approximated by a linear model, then linear regression is going to work well and outperform an approach such as decision trees which exploit nonlinear and complex relationship between the outcome and features. In the case such as a particular pupil's success in an upcoming exam, as well as prediction of it, is likely to be affected by a set of features in nonlinear and complex ways, relative performance of decision trees (ensemble methods) may be superior than classical approach. In the following; concepts of bagging, random forest and boosting methods which aggregate many decision trees to improve prediction performance are briefly introduced.

2.5.3.1. Bagging (Bootstrap Aggregation)

Bagging (Bootstrap Aggregation) is a procedure to reduce the variance of a single decision tree. At first, several subsets are created from training sample by choosing randomly with replacement. Then, each subset is used to grow their own decision tree. Each of those trees has high variance yet low bias and averaging them reduces the variance:

$$\hat{f}_{bag}(x) = \frac{1}{B}\sum_{b=1}^{B}\hat{f}^{*b}(x) \tag{2.10}$$

where B is the number of bootstrap samples chosen randomly with replacement out of training set, $\hat{f}_{bag}(x)$ is the final prediction from the bagging model for input x, $\hat{f}^{*b}(x)$ denotes the prediction of the bth decision tree for the input x, where b ranges from 1 to B.

Bagging improves prediction accuracy at the expense of interpretability since there is no single tree anymore, i.e. large number of trees are grown. In this case overall summary of each variable's importance is obtained by averaging total decrease in RSS due to partitions from a variable over all B trees. A large value indicates that it is an important variable.

2.5.3.2. Random Forest

Random Forest is an extension of bagging method which employs all variables in partitioning the data. Instead of using full set of p variables, random forest chooses a random sample of m predictors out of p as partition candidates. This allows random forest method to overcome the possibility that resulting trees look like each other i.e. they are highly correlated, and hence increased variance. For regression problems, a rule of thumb is to set $m \approx \frac{p}{3}$ and set $m \approx \sqrt{p}$ for classification problems. Consequently, bagging is a special case of random forest such that $m = p$.

2.5.3.3. Boosted Regression Tree[9]

Boosting method differs from bagging and random forest in that trees are grown sequentially using the information in previously grown trees. More specifically, observations that are previously predicted incorrectly, are chosen more often than correctly predicted observations. Therefore, boosting tries to produce new predictors that are better able to predict observations for which the current ensemble's performance is poor. James, Witten, Hastie and Tibshirani (2013, p.327) described the process of boosting for a supervised regression problems as:

1. Set $\hat{f}(x) = 0$ and $r_i = y_i$ for all i in the training set.
2. For b = 1,2,…,B, repeat:

a. Fit a tree $\hat{f}^b$ with d splits (d+1 terminal nodes) to the training data (X,r).

b. Update $\hat{f}$ by adding a shrunken version of the new tree:

$$\hat{f}(x) \leftarrow \hat{f}(x) + \lambda \hat{f}^b(x)$$

c. Update the residuals:

$$r_i \leftarrow r_i - \lambda \hat{f}^b(x_i)$$

[9] For more details on this topic, see p.337 in Chapter 10 of The Elements of Statistical Learning (Hastie, Tibshirani, & Friedman, 2009).

3. Output the boosted model,

$$\hat{f}(x) = \sum_{b=1}^{B} \lambda \hat{f}^{b}(x).$$

where λ is the shrinkage parameter (learning rate) and d is the number of splits (depth of a tree).

2.6. Results

This study compared between three supervised machine learning modelling methods (i.e. Decision Trees, Regularization Models and Linear Regression) in terms of their predictive performances on Turkish secondary school students' academic performance in mathematics, science and reading subject areas of PISA 2018. Before estimation, the whole sample of 3876 observations are split into a 80% training set and 20% test set. For all methods, 10-fold cross validation is performed on the training set (i.e. the model is estimated on the training set) and related hyperparameters of the model is determined. The predictive performance of each model is evaluated on the test set by the measure of mean squared error.

2.6.1. Test Sample Prediction Performance of Each Model

All models had a single set of plausible value for each subject as their response variable (i.e. PV1MATH, PV1SCIENCE, PV1READ). Besides, all models had 71 input variables at student- and school levels. It is important to note that main results presented here are related to directly measurable variables at student and school levels. In other words, student-perceptional and -attitudinal variables which cannot be directly measured are excluded in the prediction of student academic achievement. Seven models, namely multiple linear regression, ridge regression, LASSO, elastic net regression, bagging, random forest and boosting models are trained on the training set; which corresponds to 80% of whole data; and then their prediction accuracy is evaluated on the test set; which constitutes rest of the data; based on the measure of Mean Squared Error. Table 2.6, Table 2.7 and Table 2.8 summarize mean squared errors calculated based on each model in the test sample. It is apparent from these tables that, boosted regression tree (BRT) model produces the best predictive performance for Turkish secondary school students' subject literacy in mathematics, science and reading.

Table 2.6. Prediction Accuracy of Models for Turkish Students' Mathematics Performance

Method	Mean Squared Error in Test Sample
Linear Regression	10460.22
Ridge Regression	3480.442
LASSO	3425.665
Elastic Net	3366.339
Bagging	3805.494
Random Forest	3038.675
BRT	**2745.782**

Note: Model in bold indicates the best predictive performance

Table 2.7. Prediction Accuracy of Models for Turkish Students' Science Performance

Method	Mean Squared Error in Test Sample
Linear Regression	8886.334
Ridge Regression	2839.41
LASSO	2891.566
Elastic Net	2824.739
Bagging	3474.429
Random Forest	2595.649
BRT	**2421.81**

Note: Model in bold indicates the best predictive performance

Table 2.8. Prediction Accuracy of Models for Turkish Students' Reading Performance

Method	Mean Squared Error in Test Sample
Linear Regression	9776.205
Ridge Regression	3432.07
LASSO	3430.31
Elastic Net	3398.811
Bagging	3731.695
Random Forest	3040.552
BRT	**3033.227**

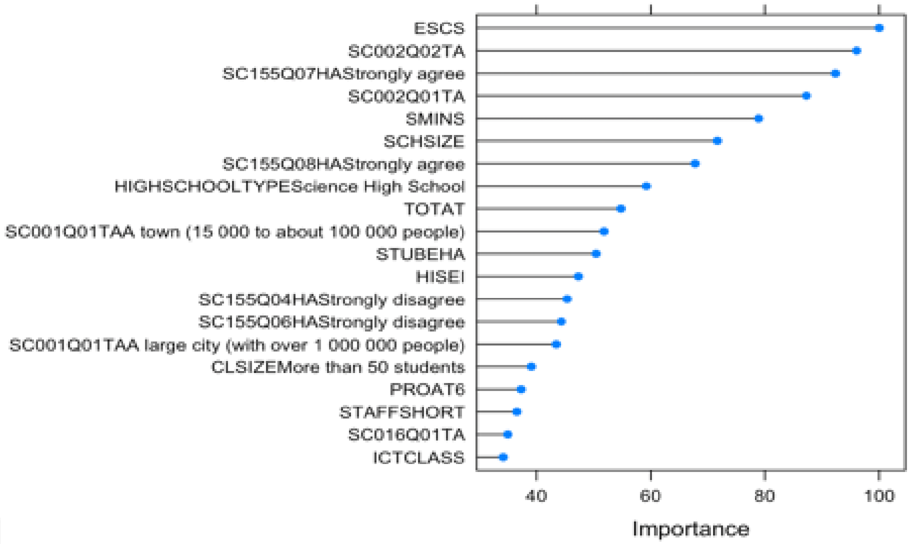
Note: Model in bold indicates the best predictive performance

2.6.2. Variable Importance Indicated by Decision Tree Models

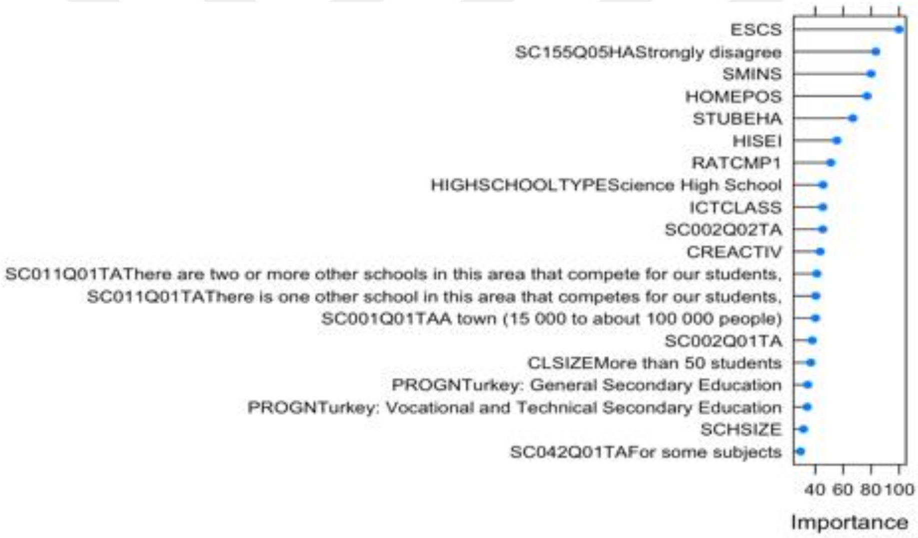
In order to predict Turkish secondary school students' performance Bagging, Random Forest and Boosted Regression Trees are fit to Turkish subset of PISA 2018 data for each subject. Figure 2.14 and Figure 2.15 depict the top 20 most important variables that come forward in the prediction of student success in mathematics, science and reading subjects of PISA 2018 according to bagging model and random forest model, respectively. The bagging model implies that the most important features that have the highest predictive effect on a Turkish student's mathematics performance in PISA exam are found as index reflecting student's economic, cultural and social status (ESCS), number of girls in school (SC002Q02TA), school's capacity using digital devices (SC155Q07HA and SC155Q08HA-Strongly agree), number of boys in school (SC002Q01TA), student's science learning time -minutes per week- (SMINS), school size (SCHSIZE), type of highschool (HIGHSCHOOLTYPE – Science), total number of teachers at school (TOTAT), school location (SC001Q01TA- A town of 15000 to 100000 people), student behavior hindering learning (STUBEHA), highest parental occupational status (HISEI), school's capacity using digital devices (SC155Q04HA and SC155Q06HA-Strongly disagree), school location (SC001Q01TA- A large city of over 1000000 people), class size at school (CLSIZE-More than 50 students), proportion of teachers with ISCED level 6 (PROAT6), shortage of educational staff (STAFFSHORT), school funding (SC016Q01TA- Government), subject related ICT use during lessons (ICTCLASS). For the prediction of science performance of a Turkish student; as different from mathematics subject; possessions at home (HOMEPOS), number of available computers per student (RATCMP1), extra-curricular creative activities at school (CREACTIV), competition from other schools (SC011Q01TA-One or more competing schools), school programme type (PROGN-General Secondary Education and Vocational and Technical Education) and school's policy for grouping students into classes based on ability (SC042Q01TA-For some subjects) matter the most. Finally; in order to predict reading performance of a Turkish student, school's policy for grouping students into classes based on ability (SC042Q01TA-Not for any subject), use of ICT at school in general (USESCH), student-teacher ratio (STRATIO), school's capacity using digital devices (SC155Q02HA and SC155Q05HA-Strongly agree) and student's ICT use outside of school for leisure (ENTUSE) come forward as different from mathematics and science subjects. To sum, according to bagging model, for each subject area, a combination of student and school level characteristics emerge as major features for prediction.

Figure 2.14. Bagging Variable Importance Plots

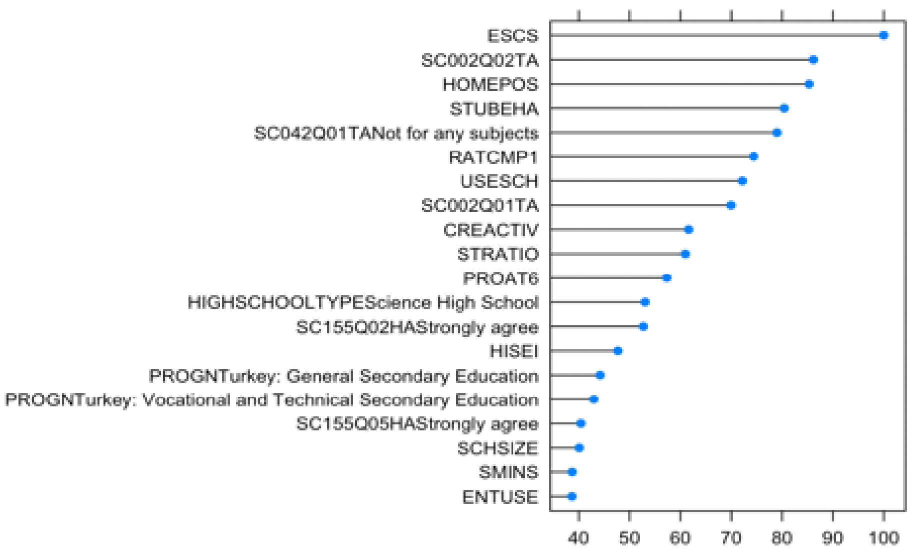
Mathematics



Science

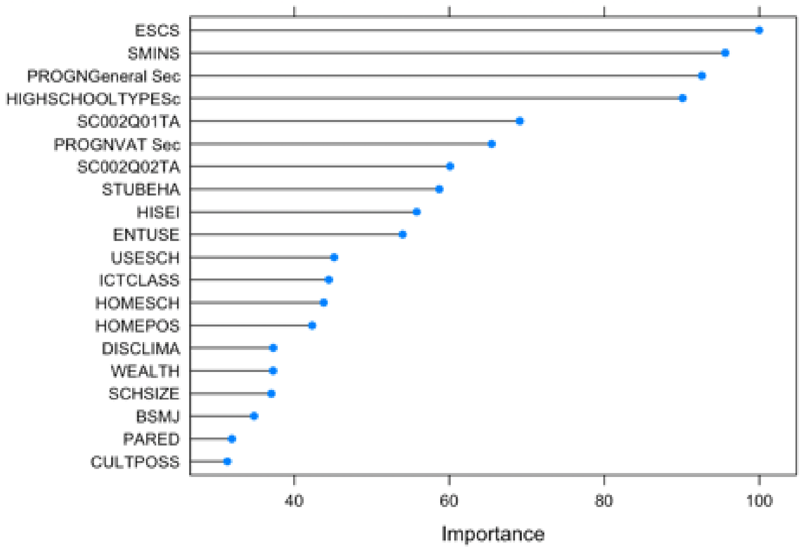


Reading

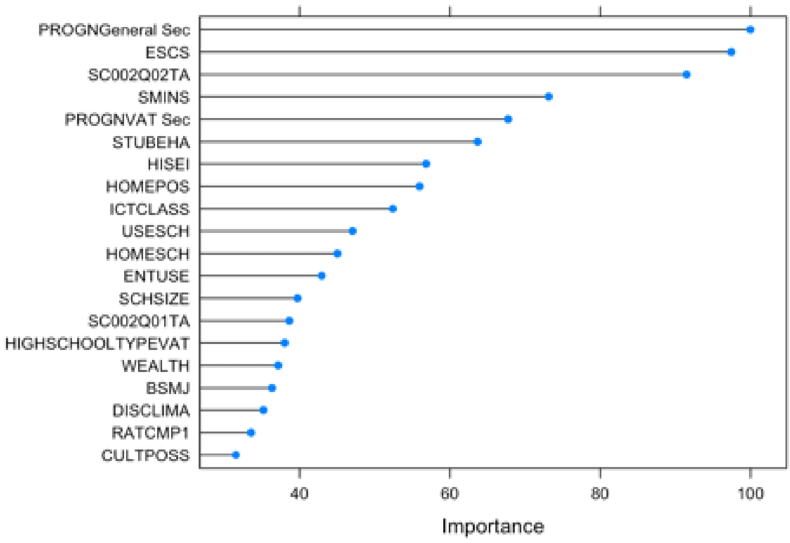


It is apparent from Figure 2.15 that according to random forest model the most influential features that have the highest predictive effect on a Turkish student's mathematics performance in PISA exam are found as index reflecting student's economic, cultural and social status (ESCS), student's science learning time -minutes per week- (SMINS), school programme type (PROGN-General Secondary Education and Vocational and Technical Education), type of highschool (HIGHSCHOOLTYPE – Science), number of girls in school (SC002Q02TA), number of boys in school (SC002Q01TA), highest parental occupational status (HISEI), student behavior hindering learning (STUBEHA), student's ICT use outside of school for leisure (ENTUSE), use of ICT at school in general (USESCH), subject related ICT use during lessons (ICTCLASS),student's use of ICT outside of school for schoolwork activities (HOMESCH), possessions at home (HOMEPOS), disciplinary climate in lessons (DISCLIMA), familial wealth (WEALTH), school size (SCHSIZE), student's expected occupational status (BSMJ), cultural possessions at home (CULTPOSS) and subject related ICT use outside lessons (ICTOUTSIDE). In addition to these characteristics, number of available computers per student (RATCMP1) is found as significant in predicting students' science achievement in Türkiye. For predicting reading success of students in Türkiye in addition to aforementioned variables, ICT availability at school (ICTSCH) and number of available computers per student (RATCMP1) are pointed out by random forest model.

Figure 2.15. Random Forest Variable Importance Plots Mathematics



Science



Reading

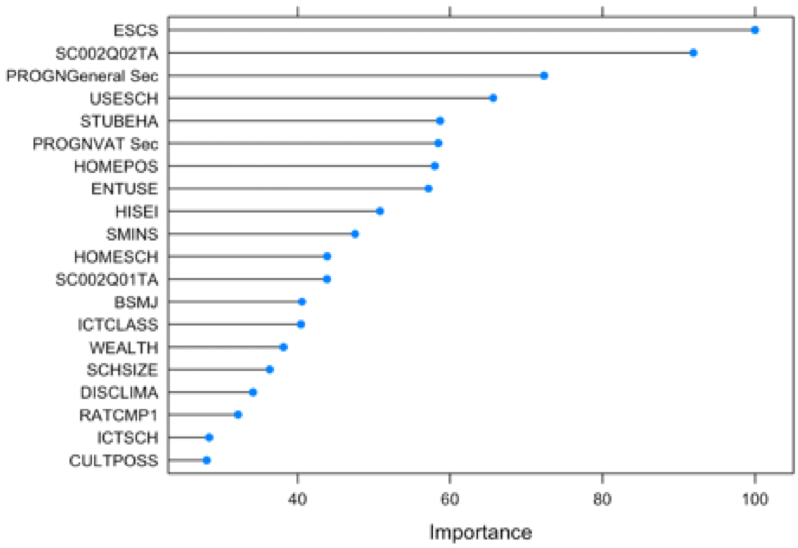


Table 2.9 summarizes results from 10 fold cross-validation for boosting method on the training set for each subject of PISA. Accordingly, a grid of hyperparameters[10] are constructed and boosted regression tree is grown for each combination of hyperparameters and mean squared errors are calculated and noted for each round. The combination of hyperparameters which produced the smallest Mean Squared Error is chosen.

[10] The set of hyperparameters for learning rate is: {0.05, 0.1, 0.2, 0.5} for depth of the tree: {1, 2, 3, 4, 5} for number of trees: {1000, 2000, 5000, 10000}.

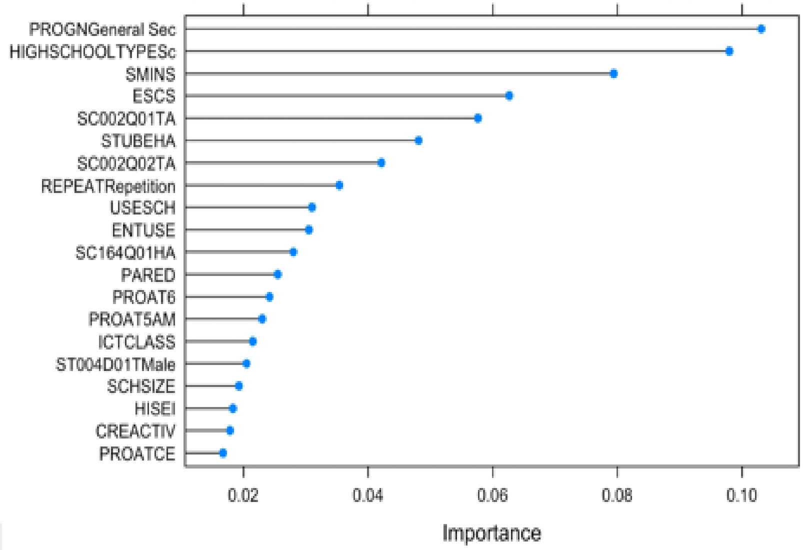
Table 2.9. 10 fold CV Results of BRT Method

	Mathematics	Science	Reading
Learning Rate	0.1	0.05	0.05
Depth	1	2	2
Number of Trees	2000	1000	1000

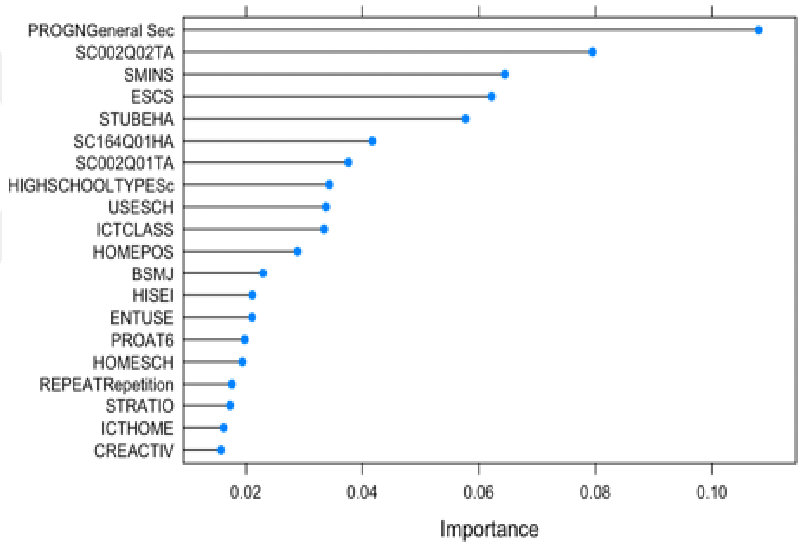
Figure 2.16 plots relative influences from top twenty important variables as implied by boosting model. Each plot in Figure 2.17 stands for mathematics, science and reading subjects, respectively. BRT model produces the similar results for students' literacy in each subject as in bagging and random forest models. Accordingly, type of highschool (HIGHSCHOOLTYPESc – Science), the index of economic, social and cultural status (ESCS), student's science learning time -minutes per week- (SMINS), school programme type (PROGN-General Secondary Education), number of boys' enrollment to the school (SC002Q01TA), student behavior hindering learning (STUBEHA), number of girls' enrollment to the school (SC002Q02TA), student's status of grade repetition in the past (GRADE REPETITION), use of ICT at school in general (USESCH), percentage of recent school dropout (SC164Q01HA), use of ICT for leisure (ENTUSE), parental education in years (PARED), proportion of teachers with ISCED level 6 (PROAT6), proportion of teachers with degree ISCED level 5-Master (PROAT5AM), subject related ICT usage in class during lessons (ICTCLASS), student's gender (ST004D01T-Male), number of students in the school (SCHSIZE), existence of creative extra-curricular activities (CREACTIV), proportion of fully certified teachers (PROATCE), highest parental occupational status (HISEI) emerge as influential in prediction of mathematical literacy of a Turkish student. For the prediction of scientific literacy of a Turkish student, in addition to previously emphasized characteristics which are mentioned for mathematics except for gender, proportion of certified teachers, girls' enrolment and school size; student's expected occupational status (BSMJ), student's home possessions (HOMEPOS) and student-teacher ratio (STRATIO) matter the most. In order to predict reading literacy of a Turkish pupil; similar to science literacy, student's home possessions (HOMEPOS), student's expected occupational status (BSMJ) and student-teacher ratio (STRATIO) in addition to mathematical literacy characteristics except boys' enrolment to school, school programme type (PROGN-General Secondary Education) and general ICT availability at school (ICTSCH) come forward.

Figure 2.16. BRT Model Relative Influence Plots

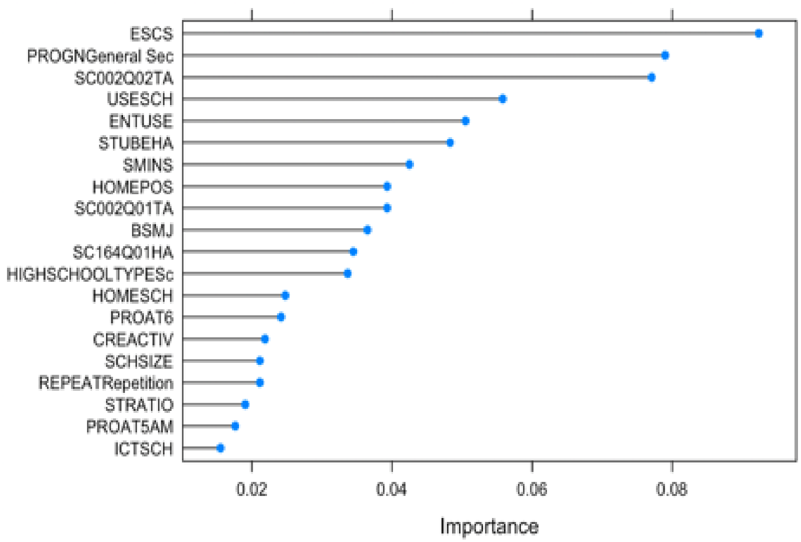
Mathematics



Science

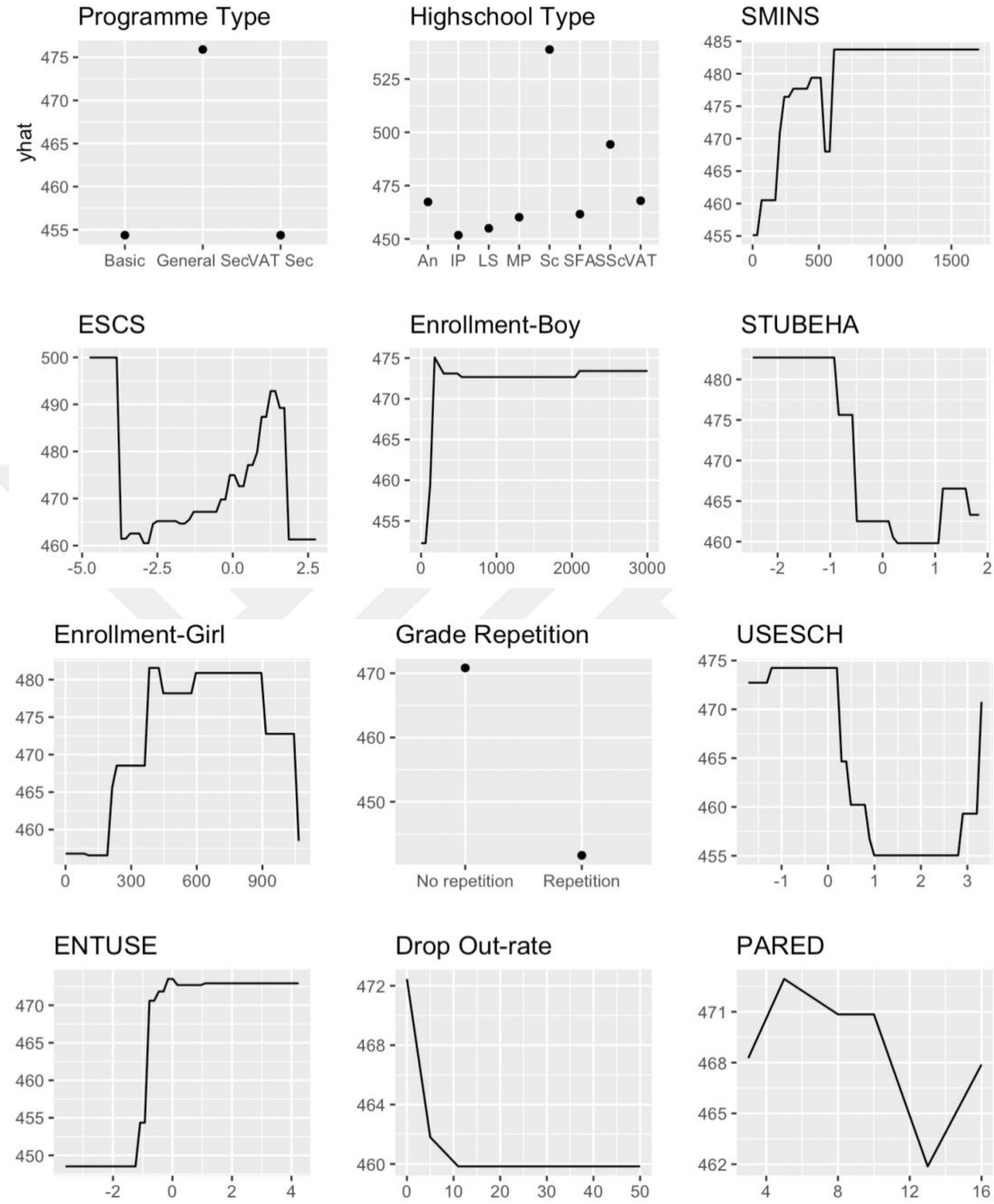


Reading



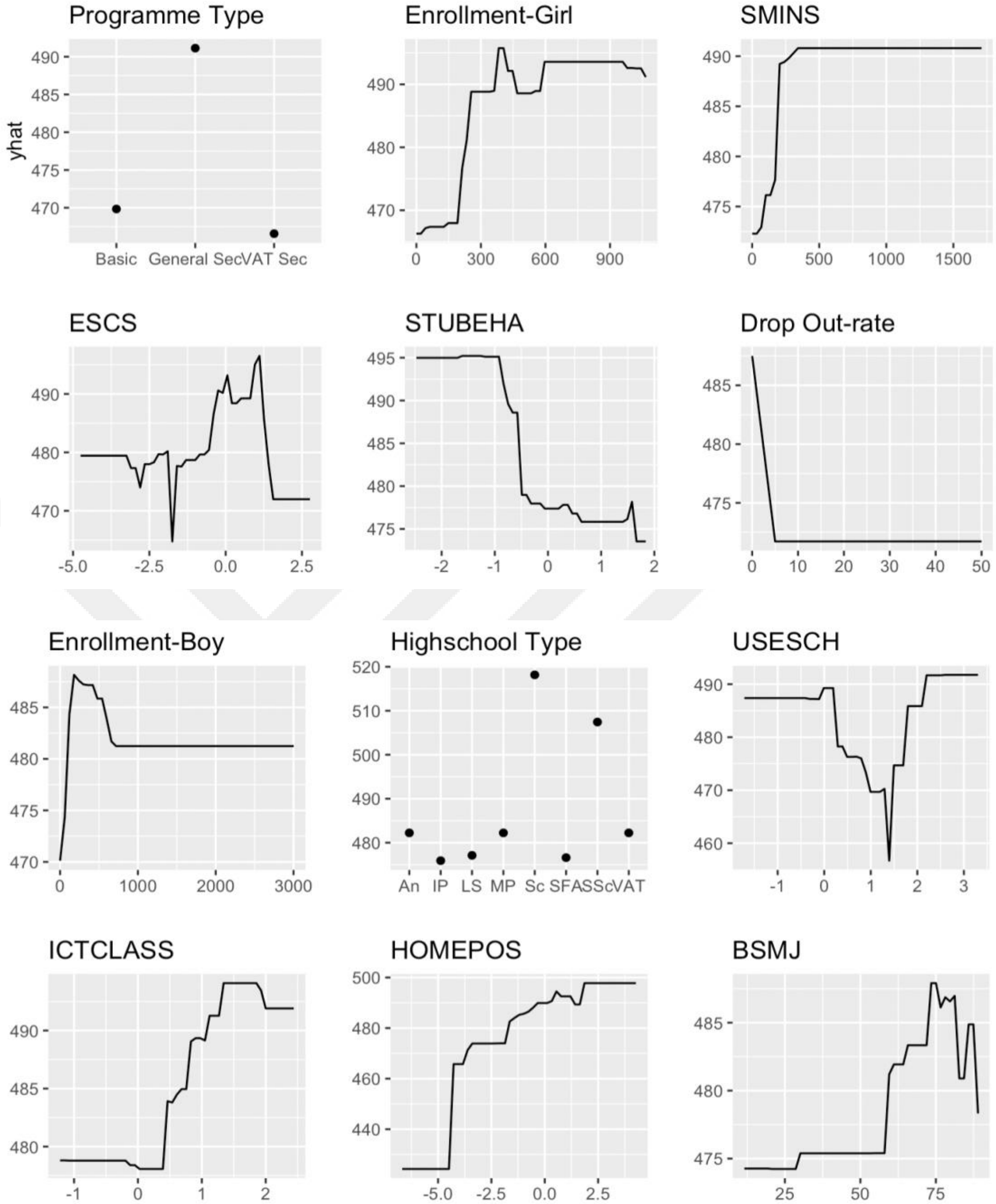
In order to investigate how values of BRT model inputs affect the model's predictions partial dependence plots, which represents a prediction for a particular value of input variable while averaging out the impact of other variables in the model, are generated. Figure 2.17, Figure 2.18 and Figure 2.19 show the relationship between top 12 student- and school-level characteristics and predicted student's achievement at PISA mathematics, science and reading subjects, respectively. School programme type which has three categories as basic education (Basic), general secondary education (General Sec) and vocational and technical education (VAT Sec) appears to be one of the most influential variable on academic achievement. For all subjects, students who are enrolled at high schools of general secondary education tend to be more successful with respect to their peers who are enrolled at other category high schools. High school type which has eight categories as Anatolian (An), Imam-Preacher (IP), Lower-Secondary (LS), Multi Programme (MP), Science (Sc), Sports-Fine Arts (SFA), Social Science (SSc) and Vocational-Technical (VAT), is another significant variable in the prediction of student success. Accordingly, the most successful students are from Science high schools followed by students from Social Science High schools and students from Anatolian High schools. Moreover, this result holds for all subject areas. Student's science learning time per week (SMINS) emerges as important in predicting student achievement in all subject areas: Turkish secondary school students' performance in each subject is increasing with weekly studying time. Student's socioeconomic background as proxied by ESCS index of PISA which is a composite standardized measure reflecting highest parental occupation, parental education and home possessions including number of books at home is another variable stressed by BRT model as important in the prediction of student success in all subjects. Higher ESCS values are associated with higher predicted student scores up to one standard deviation ahead the mean. After that, student's scores in mathematics and science -except reading- are predicted to decline. Boys' enrollment to school is associated with higher predicted mathematics scores yet for science and reading scores girls' enrollment to school is much more important. Student behavior hindering learning (STUBEHA) appears to be another important predictor of student success. Smaller values of the index reflects no/little existence of student behavior hindering learning whereas higher values are associated with frequent occurrence of the event. The school drop-out rate seems to be negatively related to student performance prediction for all subjects. Student's grade repetition status appears to be related to prediction of mathematics performance such that student's experience of grade repetition in the past is associated with lower predicted mathematics score. Finally, ICT availability and usage come forward in prediction of Turkish student scores. ICT-related variables are standardized such that mean score is 0 and standard deviation is 1 (OECD, 2019). Therefore, it can be said that students with negative values are below the average, students with positive values are above the average and students with value of 0 is in the average in relevant category. According to partial dependence plots, the relationship between use of ICT at school in general (USESCH) and predicted student scores in mathematics and science subjects is U-shaped, whereas it is a negative relationship between the former and reading subject. Students using ICT outside of school for leisure activities (ENTUSE) above the average are predicted to score higher in mathematics and science yet no such indication can be derived for reading subject. Similarly, students with above the average usage of subject related ICT (ICTCLASS) during lessons are predicted to score higher in science. For reading, students with above the average home endowments (HOMEPOS) are predicted to score higher. For reading and science, BRT model estimates a step function for student's expected future occupational status index (BSMJ), where higher values are associated with higher occupational status.

Figure 2.17. Partial Dependence Plots of Top 12 variables from BRT for Mathematics



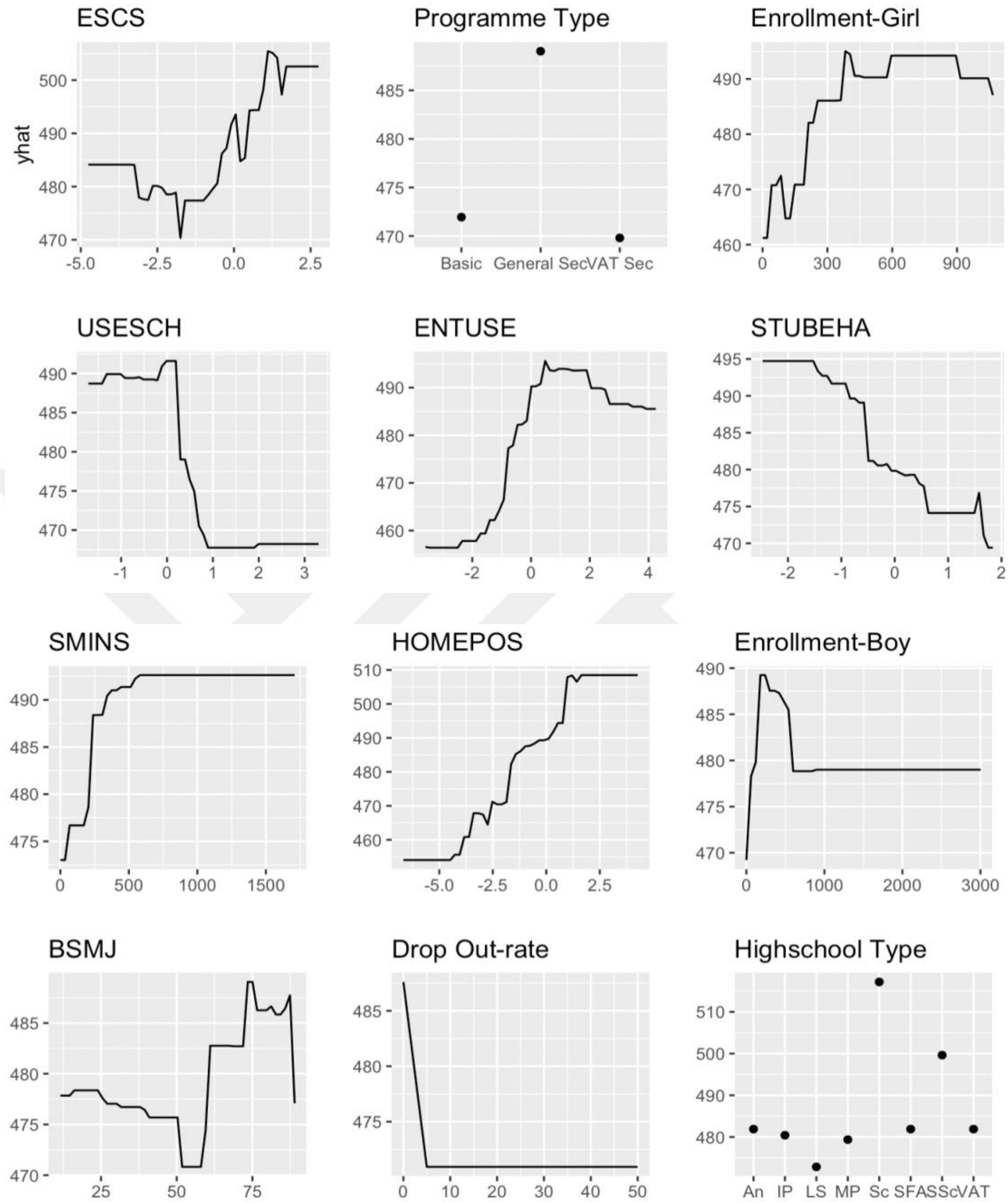
Note: An: Anatolian Highschool, IP: Imam-Preacher Anatolian Highschool, LS: Lower Secondary School, MP: Multi Programme Highschool, Sc: Science Highschool, SFA: Sports and Fine Arts Highschool, SSc: Social Science Highschool, VAT: Vocational and Technical Highschool. yhat stands for prediction of student mathematics achievement in PISA 2018.

Figure 2.18. Partial Dependence Plots of Top 12 variables from BRT for Science



Note: An: Anatolian Highschool, IP: Imam-Preacher Anatolian Highschool, LS: Lower Secondary School, MP: Multi Programme Highschool, Sc: Science Highschool, SFA: Sports and Fine Arts Highschool, SSc: Social Science Highschool, VAT: Vocational and Technical Highschool. yhat stands for prediction of student science achievement in PISA 2018.

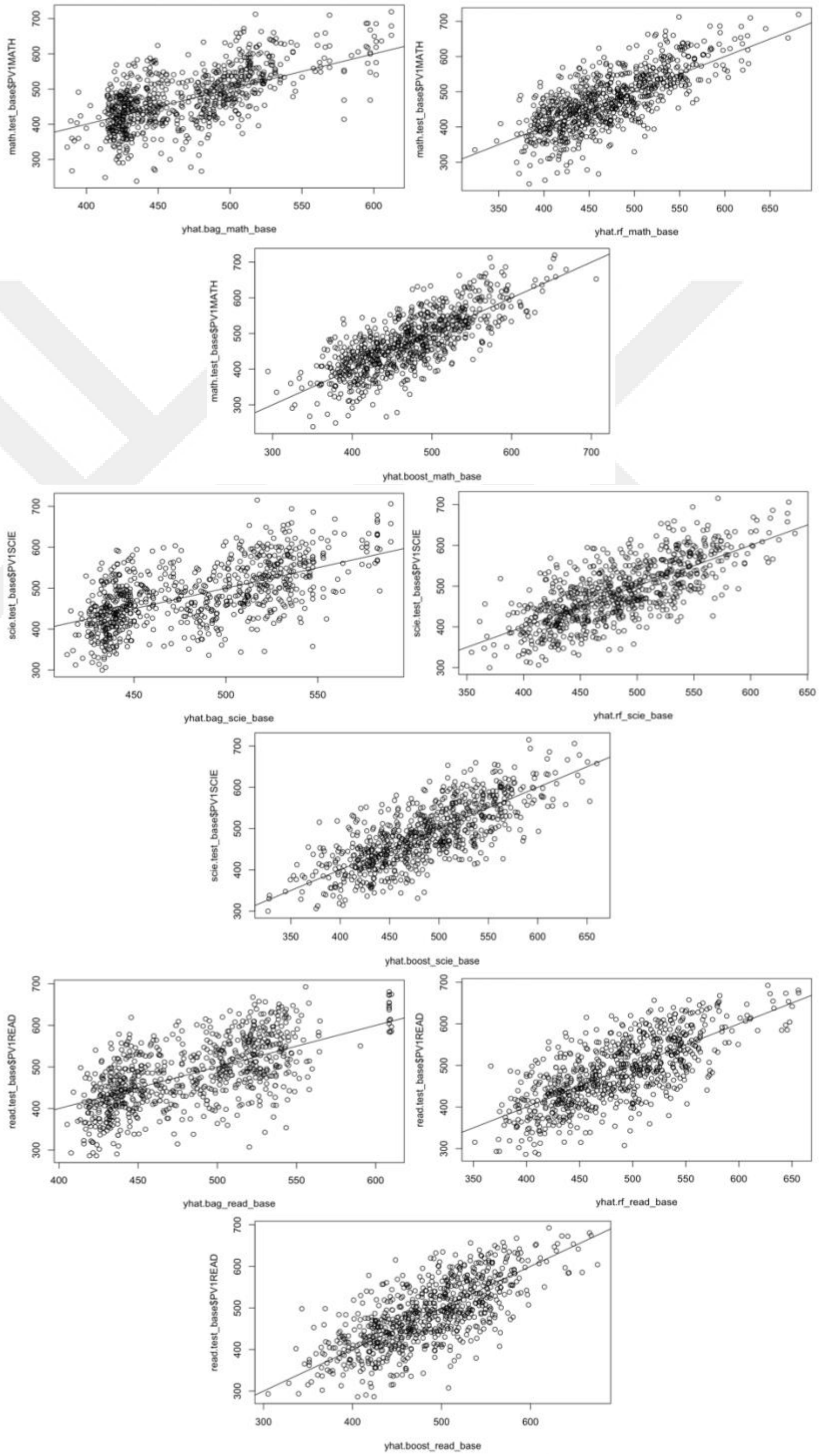
Figure 2.19. Partial Dependence Plots of Top 12 variables from BRT for Reading



Note: An: Anatolian Highschool, IP: Imam-Preacher Anatolian Highschool, LS: Lower Secondary School, MP: Multi Programme Highschool, Sc: Science Highschool, SFA: Sports and Fine Arts Highschool, SSc: Social Science Highschool, VAT: Vocational and Technical Highschool. yhat stands for prediction of student reading achievement in PISA 2018.

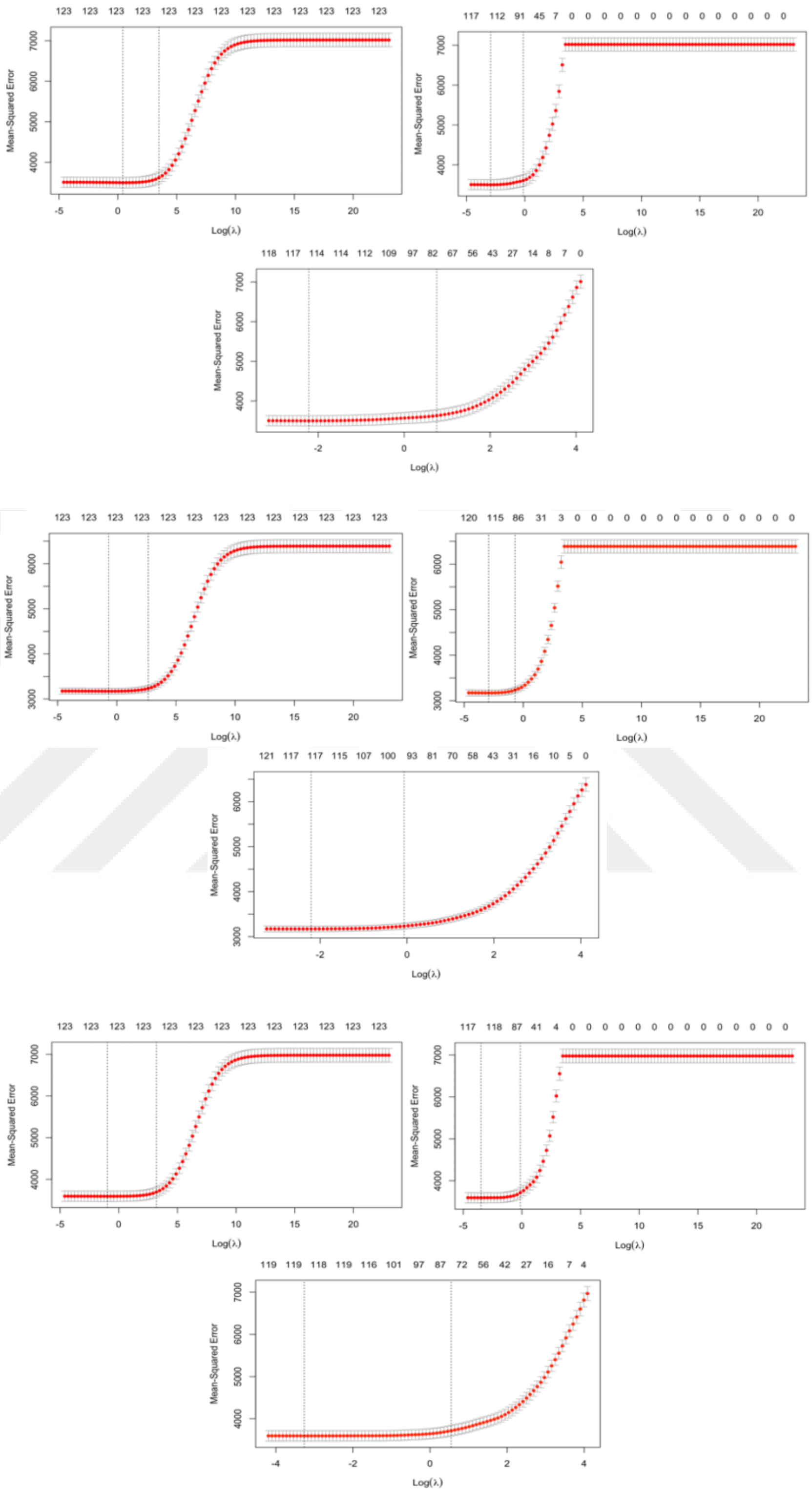
In order to perform a visual inspection of the goodness of fit, 20% of whole data was retained to test each model on unseen data and the actual scores of test set were plotted against the predicted scores from each decision tree model. Relatedly, Figure 2.20 illustrates the prediction accuracy of each decision tree model namely; bagging, random forest and boosting for each subject area in PISA test. The y-axis shows actual values in test set whereas the x-axis shows predicted values for the same set from related model. In terms of error magnitude, random forest and boosting models seem to perform similarly to each other and better than bagging model across the range of each subject's scores.

Figure 2.20. Scatter Plots for Prediction Accuracy of Decision Tree Models



Note: Mathematics, Science, Reading from top to bottom. Bagging, Random Forest, BRT; in order.

Figure 2.21. 10-fold Cross Validation Results of the Relationship Between MSE and log(λ)



Note: From left to right: Ridge Regression, LASSO, Elastic Net; From top to bottom: Mathematics, Science, Reading

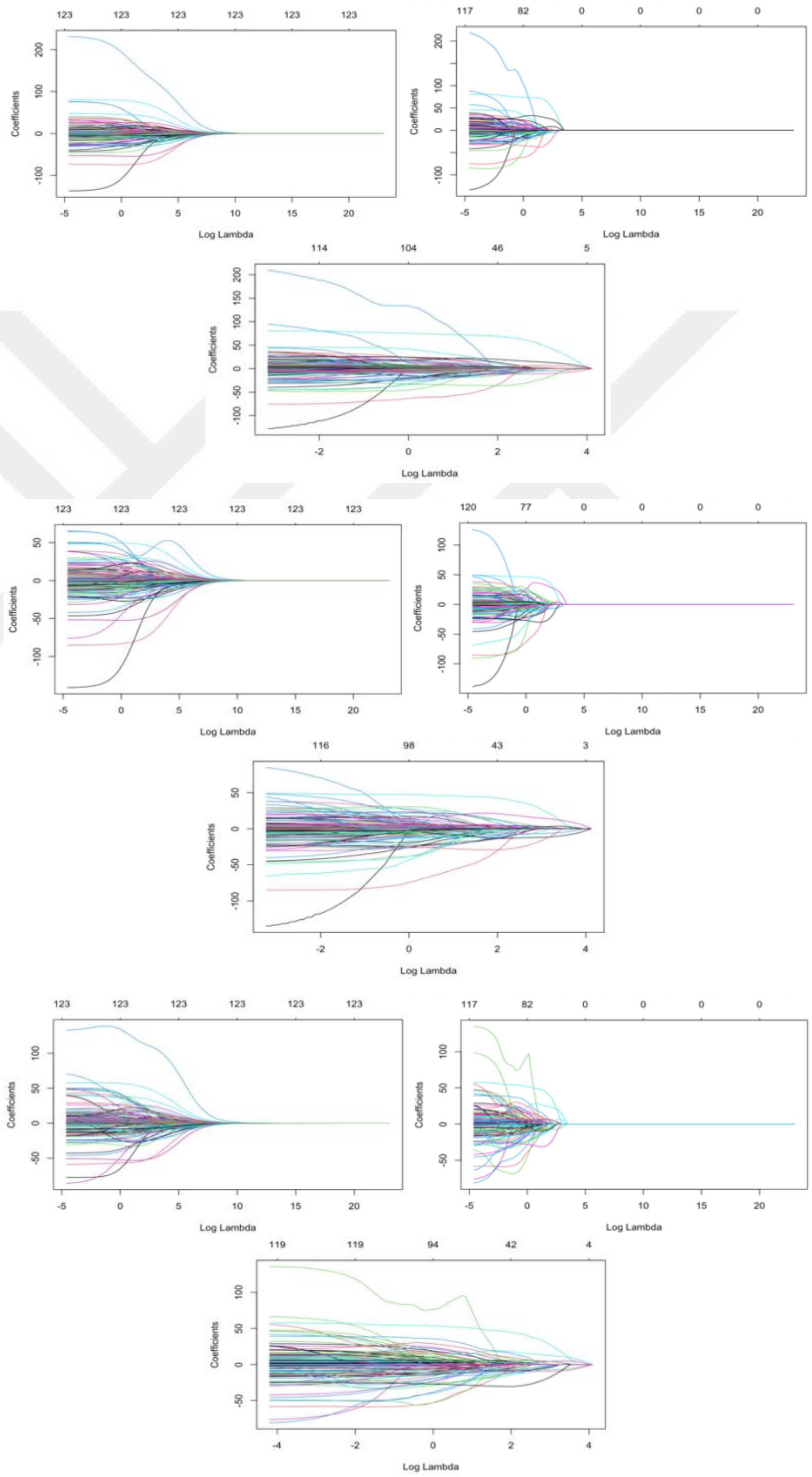
Figure 2.21 shows the 10-fold CV results of Mean Squared Error (MSE) measure from left to right: Ridge, LASSO and Elastic Net regressions for each subject area from top to bottom: mathematics, science and reading subject areas. The numbers just above each box stand for the number of non-zero coefficients with corresponding log(λ) values on the x-axis. The vertical dotted line on the left in each box indicate the λ value that yields the minimum cross-validated MSE (i.e. lower bound), and the vertical dotted line on the right in each box indicate λ value that yields the cross-validated MSE which is within one-standard error of the minimum cross-validated MSE (i.e. upper bound). For mathematics subject, the number of non-zero coefficients that remain in the model according to λ value[11] which yields minimum cross-validated MSE is the lowest for Elastic Net model (number of non-zero coefficients is equal to 78), followed by the LASSO model (number of non-zero coefficients is equal to 82) and then the Ridge Regression model (number of non-zero coefficients is equal to 123). For science subject, the number of non-zero coefficients that remain in the model according to λ value[12] which yields minimum cross-validated MSE is the lowest for LASSO (number of non-zero coefficients is equal to 92), followed by Elastic Net model (number of non-zero coefficients is equal to 98) and then the Ridge Regression model (number of non-zero coefficients is equal to 123). For reading subject, the number of non-zero coefficients that remain in the model according to λ[13] value which yields minimum cross-validated MSE is the lowest for Elastic Net model (number of non-zero coefficients is equal to 82), and for LASSO (number of non-zero coefficients is equal to 82) followed by the Ridge Regression (number of non-zero coefficients is equal to 123). Therefore, the most parsimonious model among regularization methods appears to be Elastic Net model for all subjects.

Figure 2.22 shows coefficients' paths as the value of shrinkage parameter, λ increases from left to right: Ridge, LASSO and Elastic Net regressions for each subject area from top to bottom: mathematics, science and reading subject areas. The

[11] For mathematics subject; λ value which yields minimum cross-validated MSE for Ridge Regression is equal to 32.75, for LASSO is equal to 0.8697, for Elastic Net is equal to 2.1326.
[12] For science subject; λ value which yields minimum cross-validated MSE for Ridge Regression is equal to 14.175, for LASSO is equal to 0.4977, for Elastic Net is equal to 0.9344.
[13] For reading subject; λ value which yields minimum cross-validated MSE for Ridge Regression is equal to 24.771, for LASSO is equal to 0.8697, for Elastic Net is equal to 1.7333.

numbers just above each box stand for the number of non-zero coefficients with corresponding log(λ) values on the x-axis. The values on the y-axis indicates the coefficients of predictors. We can see that for all subject areas and for all regularization methods, the coefficients tend towards 0 as λ increases.

Figure 2.22. Shrinkage Parameter (λ) and Corresponding Model Coefficients



Note: From left to right: Ridge Regression, LASSO, Elastic Net; From top to bottom: Mathematics Subject, Science Subject, Reading Subject.

2.6.3. Turkish Students' Academic Achievement by High School Types

Given the insights provided by the BRT model, it becomes evident that for Turkish students high school type stands out as a paramount factor influencing student achievement across all subject areas in the PISA 2018 test. This naturally prompts the question: How do these predictors of student achievement evolve concerning different types of high schools? To explore this phenomenon, we undertake a comparative analysis, using the identical methodology of BRT with a 10-fold CV, focusing on the two most commonly enrolled and the most successful highschools namely VAT, Anatolian and Science.

Table 2.10 summarizes results from 10 fold CV for BRT method on the training set for each subject and for VAT, Anatolian and Science highschools. Similar to the previous execution, a grid of hyperparameters[14] are constructed and BRT is grown for each combination of hyperparameters and the combination of hyperparameters which produced the smallest MSE is chosen.

Table 2.10. 10 fold CV Results for BRT Method by Highschool Type

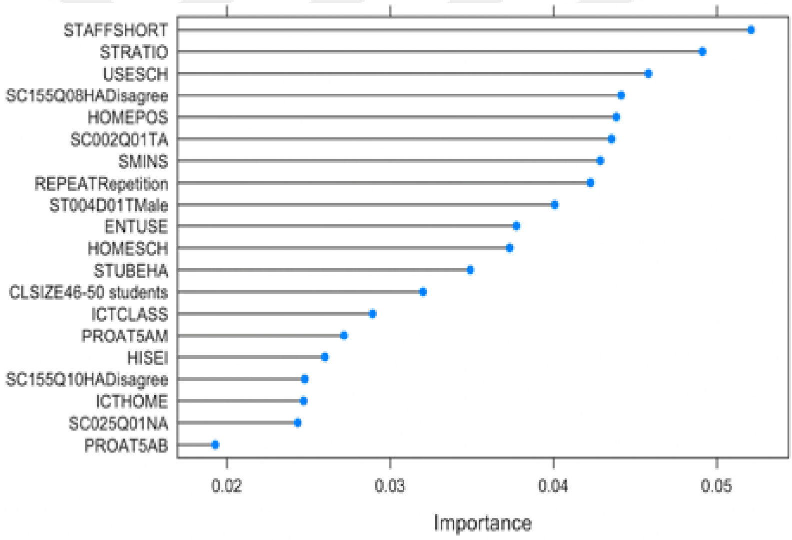
VAT Highschool			
	Mathematics	Science	Reading
Learning Rate	0.05	0.05	0.05
Depth	1	1	1
Number of Trees	1000	1000	1000
Anatolian Highschool			
	Mathematics	Science	Reading
Learning Rate	0.05	0.05	0.05
Depth	1	1	4
Number of Trees	2000	1000	1000
Science Highschool			
	Mathematics	Science	Reading
Learning Rate	0.1	0.1	0.05
Depth	4	5	1
Number of Trees	1000	1000	1000

[14] See Footnote 10.

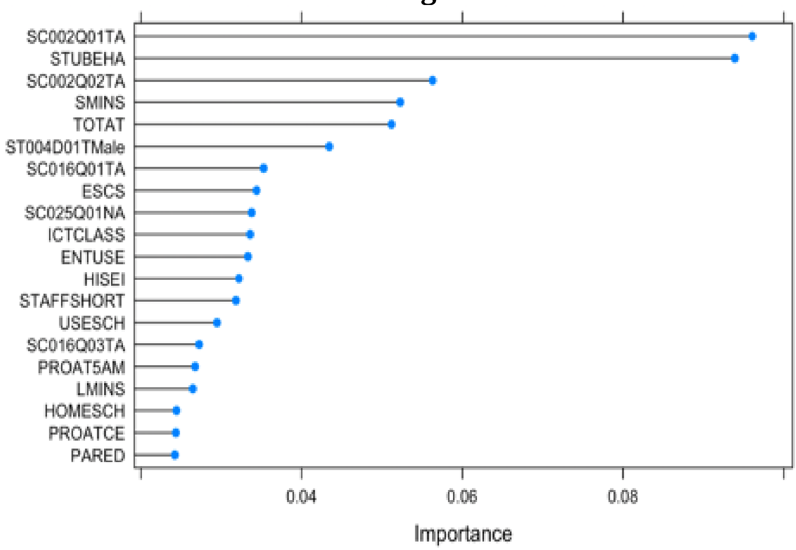
Figure 2.23 plots relative influences from top twenty important variables for the prediction of mathematics achievement of students from VAT, Anatolian and Science highschools as implied by BRT. In order to predict the mathematics achievement of Turkish students who are enrolled at VAT highschools, shortage of educational staff , student-teacher ratio, ICT availability and usage at home/school, school's capacity using digital devices, home possessions, number of boys' in the school, student's science learning time, grade repetition in the past and gender, student behavior hindering learning, class size, proportion of teachers with degree ISCED level 5-Master, parental occupation, percentage of teaching staff attended a professional development programme and proportion of teachers with degree ISCED level 5A-Bachelor emerge as influential.

Figure 2.23. BRT Relative Influence Plots for Mathematics by Highschool Type

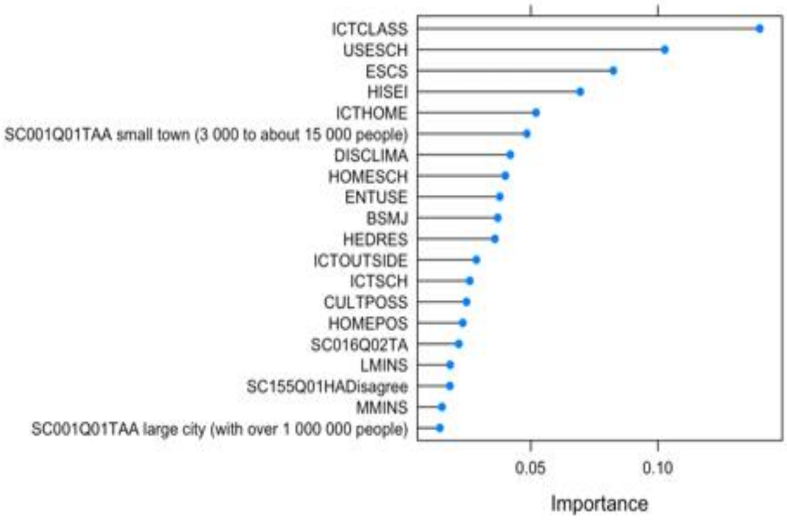
Vocational and Technical High schools



Anatolian High schools



Science High schools



Similar to VAT highschool students, the predictors of Anatolian highschool students' mathematics performance are mostly related to number of boys' enrolment to the school, student behavior hindering learning, to number of girls' enrolment to the school, student's science learning time, total number of teachers at school, student's gender, percentage of total funding of school, socioeconomic status, percentage of teaching staff attended a professional development programme, ICT usage at home/school, parental occupation and education, shortage of educational staff, proportion of teachers with degree ISCED level 5-Master, student's reading learning time, proportion of certified teachers. For the two most commonly enrolled highschool types, twelve out of twenty most important characteristics are school related. In fact they are in essence indicators of quality of education in those schools such that quality of teachers (i.e. their education, their status of attendance to professional development programs etc.), school's facility to enable better education such that class size, ICT availability and usage etc.

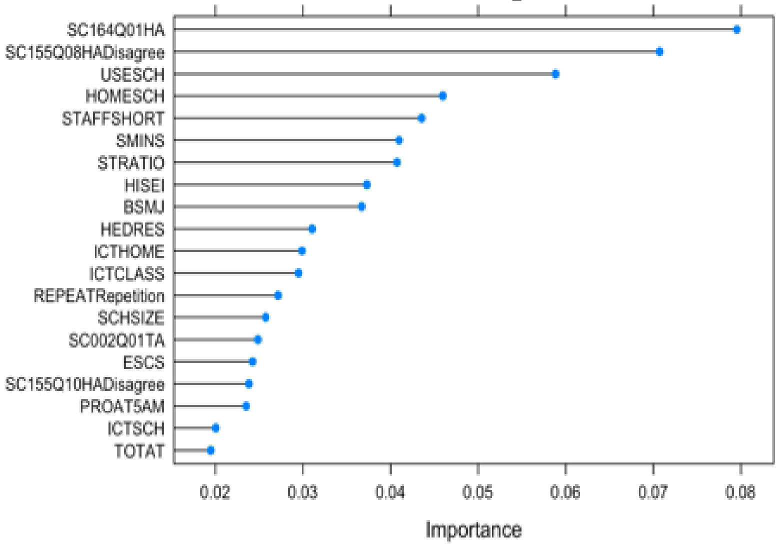
For the Science highschool students' mathematics performance it is observed that eleven out of twenty most important characteristics are student based. These include socioeconomic status, parental education, ICT availability and usage at home, student's expected occupational status, home endowments as educational and cultural resources, student's reading and mathematics learning time. In terms of school-based characteristics ICT availability/usage and disciplinary climate, location of school and percentage of total funding of school appear as important in predicting science highschool students' mathematics performance.

Figure 2.24 replicates the procedure as in Figure 1.23 for science subject. In order to predict the science achievement of Turkish students who are enrolled at VAT highschools, percentage of student drop out of school, school's capacity using digital devices, ICT availability and usage at home/school, shortage of educational staff, student's science learning time, student-teacher ratio, parental education, student's occupational aspiration, home educational resources, student's grade repetition in the past, school size, number of boys in the school, socioeconomic status, proportion of teachers with degree ISCED level 5-Master and total number of teachers at school appear as important.

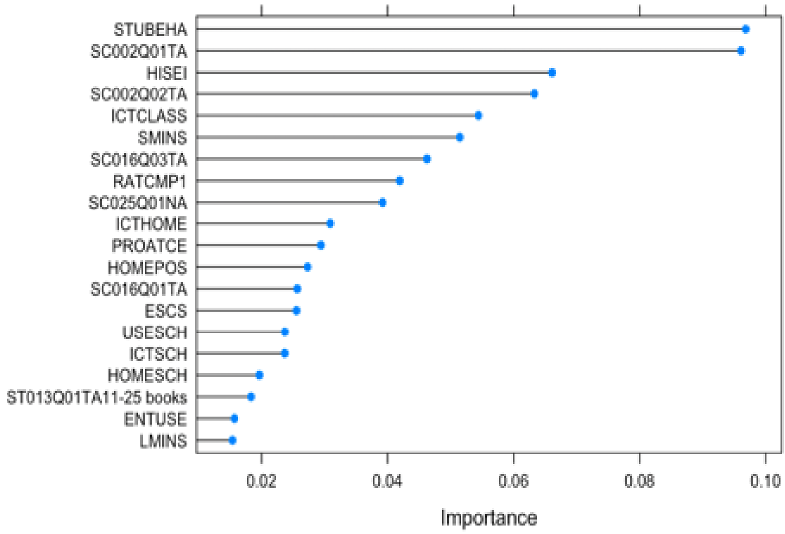
Like VAT highschool students, the predictors of Anatolian highschool students' science performance mostly include aforementioned characteristics as well as student behavior hindering learning, parental occupational status, number of available computers per student, proportion of certified teachers, home possessions and number of books at home. The prediction of science highschool students' science performance involves similar characteristics as their peers in other types of highschools and student's mathematics learning time, student's familial wealth and grade level and home cultural possessions.

Figure 2.24. BRT Relative Influence Plots for Science by Highschool Type

Vocational and Technical High Schools



Anatolian High Schools



Science High Schools

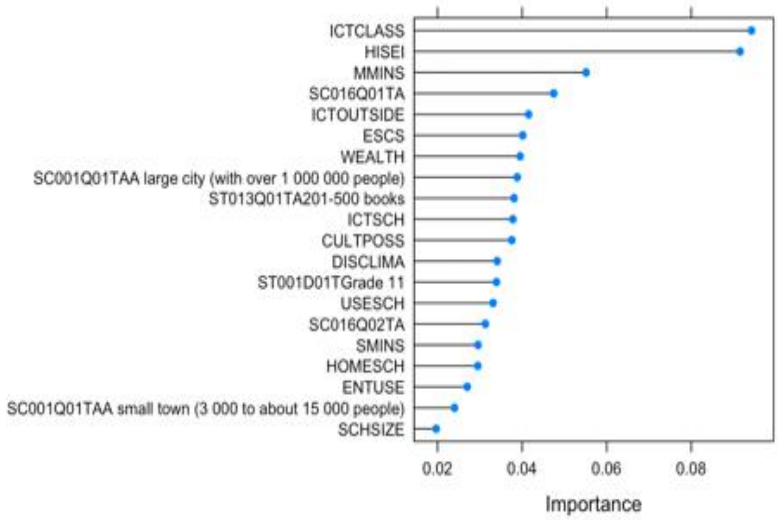
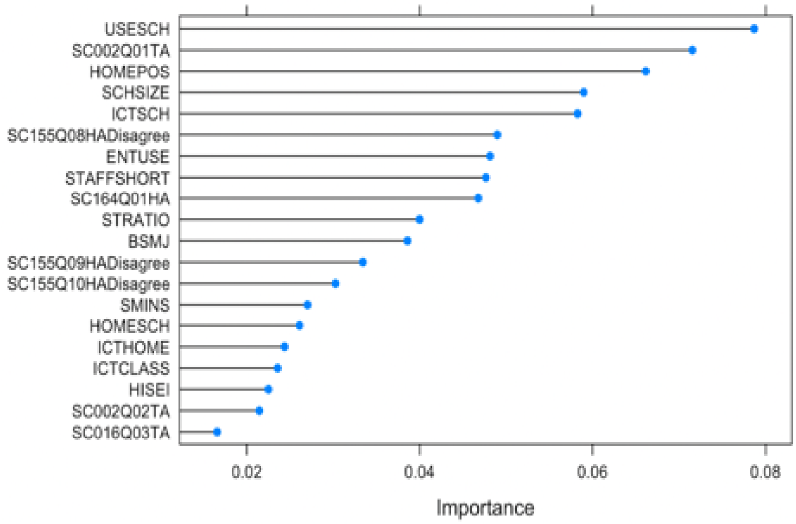


Figure 2.25 replicates the same procedure as in Figures 2.23 and 2.24 for reading subject. In order to predict reading achievement of Turkish students who are enrolled at VAT highschools, availability and usage of ICT at home/school, number of boys' in the school, home possessions, school size, school's capacity using digital devices, shortage of educational staff, the percentage of student dropout from school, student-teacher ratio, student's occupational aspiration and science learning time, parental occupation, and percentage of total funding of school come forward.

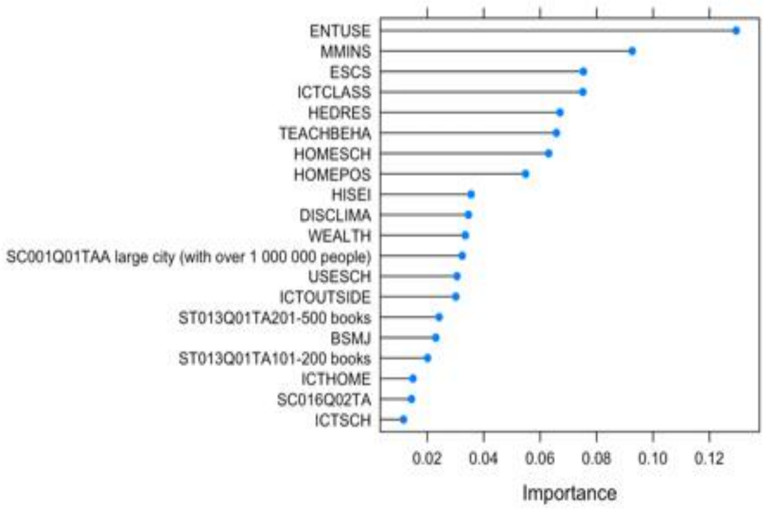
Like VAT highschool students, the predictors of Anatolian highschool students' reading performance mostly include aforementioned characteristics together with home educational resources, teacher behavior hindering learning, familial wealth, number of books at home, disciplinary climate in lessons, socioeconomic status, ICT usage and percentage of total funding of school. The prediction of science highschool students' reading performance involves similar characteristics as their peers in other types of highschools and percentage of teaching staff attended professional development and percentage of total funding of school.

Figure 2.25. BRT Relative Influence Plots for Reading by Highschool Type

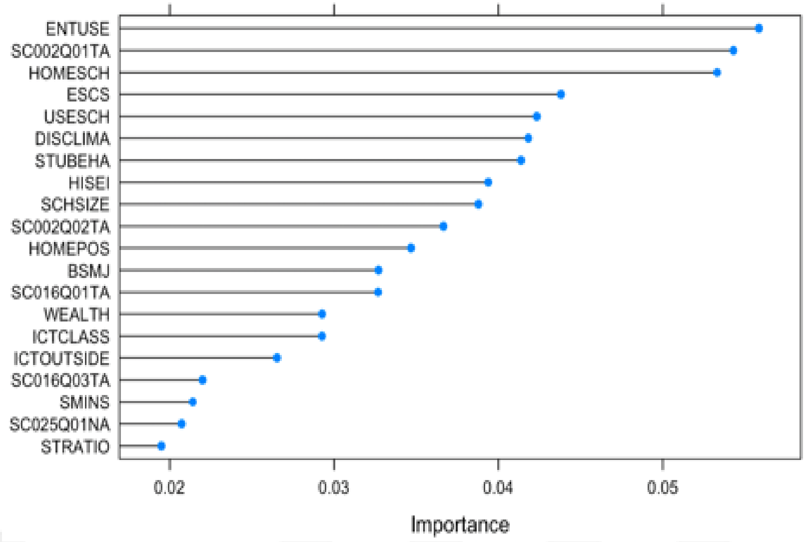
Vocational and Technical High Schools



Anatolian High Schools



Science High Schools



2.7. Discussion

This study explored educational impact of various student- family- and school-level attributes on mathematics, science and reading literacy of Turkish secondary school pupils at a well-known international large scale educational assessment test, PISA (2018) by using supervised machine learning methods. The focus of this work is two-fold: the first objective is to determine the best machine learning method which has the highest predictive accuracy in the context. The second objective is to provide evidence for the most influential variables that help predicting student success within a learning system which is highly competitive and early tracking of students is present in.

As an essential step in machine learning process whole data is split as training sample, which corresponds to 80% of whole data, and as test sample corresponding the rest. Next, 10 fold cross-validation is used to determine the hyperparameters of methods in the training sample. Then, performances of multiple linear regression, ridge regression, LASSO, elastic net regression, bagging tree, random forest and boosted regression tree methods are evaluated on the basis of Mean Squared Error (MSE) measure which is calculated on the test sample. The method which produced the smallest test sample MSE is chosen. According to results of the present study, test data performance comparison of each method reveals that regularization methods perform better than multiple linear regression and aggregated decision tree methods perform better than that of regularization methods. For each subject area in PISA 2018, boosted regression tree is chosen to be the method with the best predictive accuracy of Turkish secondary schoolers' academic performance.

Although Türkiye's average scores in each subject area increased in PISA 2018 cycle compared to the previous year, they have been below the OECD average for all cycles at which the country attended. Given that Türkiye's past performance which is not outstanding in terms of its standing with respect to other participant countries, findings from present study have important implications for exploring how to develop further advanced as well as basic literacies of Turkish young in principal subject areas. In other words, empirical evidence in this study provides educational policy makers with indications related to which of the student level and school level characteristics work to improve education performance. In doing so, Turkish young can be better targeted with educational opportunities based on their endowments at personal/ familial and school level. For all subjects, student's enrollment to schools of general secondary education instead of vocational and technical education is by far the most important in higher predicted scores of students. This result is also evident in higher predicted scores of students from Science, Social Science and Anatolian High schools. Therefore, there is still room for improvement in the nature of educational activities implemented in vocational and technical education schools.

The findings observed in this study reflect those of previous studies which investigated the predictors of student academic achievement at international student assessment tests. For example, the importance of student's economic, social and cultural status reflected by ESCS index -which is constructed by PISA based on highest parental occupation, parental education and home possessions including number of books at home- in predicting a Turkish secondary school student's success is emphasized for each subject area by boosted regression tree method. Important roles of student's socioeconomic status, home possessions, number of books at home, parental education and occupational status are also stressed in both educational production function studies (Ammermueller et al., 2005; Woessmann, 2008; Peterson & Woessmann, 2007; Şirin, 2005; Yayan & Berberoğlu, 2004; Kasapoğlu, 2014; Ferreira & Gignoux, 2010; Blanchy & Şaşmaz, 2011; Kılıç et al., 2012; Özdemir, 2016; Batyra, 2017) and educational data mining studies (Liu & Whitford, 2011; Yu et.al., 2012; Gorostiaga & Rojo-Alvarez, 2016; Martinez-Abad

& Lopez 2017; Gabriel et.al., 2018; Kılıç Depren, 2018; Masci 2018; Yoo, 2018; Dong & Hu, 2019; Filiz & Öz, 2019 Puah 2021, Hu et.al., 2022). Similarly, ICT availability and usage both at school and outside the school are emphasized by a sheer number of studies (Gorostiaga and Rojo-Alvarez, 2016; Kılıç Depren, 2018; Dong & Hu, 2019; Lee & Lee, 2021). Moreover, student's weekly learning time appears to be influential in other studies as well (Kılıç Depren, 2018; Dong & Hu, 2019; She et.al., 2019; Lee & Lee, 2021). In addition to these, emergence of student behavior hindering learning and student's future expected occupational status variables are substantiated by Lee and Lee (2021) and Hu et.al. (2022) as foremost predictors.

2.8. Conclusion

As previously highlighted throughout this study, the more proportion of educated employees the more a country's economy productive because educated employees are more able to efficiently carry out the tasks that require critical thinking and literacy. Education functions in an economy not only as raising the productivity but also as stimulating entrepreneurship and technological breakthroughs. All these factors yield greater output and economic growth in a country. Together with this motivation, this study aimed to explore the association between a sheer number of socioeconomic and demographic attributes and academic achievement of students who are close to an age of completing compulsory education in a developing country context whose population consists of a large number of young people. Prediction accuracy of different methods specifically multiple linear regression, regularization and aggregated decision trees are compared in the context of machine learning approach over Turkish subset of PISA 2018 survey.

The current findings add to growing body of literature on Educational Data Mining by providing recent evidence from a developing country with a large proportion of young population and which had recent educational reforms. Moreover, apart from previous studies the sensitivity of results are controlled by examining all subject area literacies and it is found that students from high schools of general secondary education are predicted to be more successful than their peers from other category high schools. Furthermore, this study concludes that of the twenty top most influential features, the number of student level identifiers were six, eight and seven for mathematics, science and reading subjects, respectively.

Although this study demonstrated the best machine learning method to predict Turkish secondary school students' academic achievement at a well-known international student assessment test and the most successful predictors of the outcome, it has certain limitations in terms of generalizability of the results to other exams, other countries and other years. Besides, it is important to acknowledge that these findings do not establish causal links between academic achievement of Turkish secondary schoolers and examined factors rather they present an outline of individual, family and school based attributes in which the former is prevalent. For future research, further deeper investigation of factors related to students and schools based on administrative records to clarify underlying mechanisms along with the stratified characteristic of Turkish education system is required as a progression and policy implication of current study.

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3. THE ESTIMATION AND DETERMINANTS OF AVERAGE EXPECTED SCHOOL DURATION OF TURKISH STUDENTS

3.1. Introduction

It is an educationally undesirable outcome for any student in the education system to decide not to continue their education or to leave the education process by failing to meet the requirements. The negative consequences of early leaving of schooling in monetary and non-monetary terms are emphasized by numerous studies at both individual and societal levels. At the individual level, low occupational status, low income, unemployment, poor level of living conditions, health and education for children/family, and life satisfaction, resilience and adaptability to a lesser extent are among mostly mentioned negative outcomes of school dropout. At the societal level, lower productivity, increased poverty, under-development, less social mobility, higher rates of criminal behavior, civic engagement and social cohesion to a lesser extent are the most highlighted negative consequences of school dropout (Belfield & Levin, 2007, as cited in Rumberger & Lim, 2008; Doll & Hess, 2001, as cited in Taylı, 2008; Traag & van der Velden, 2008; MEB, 2013). While negative outcomes of school dropout have been noted, a number of studies paid particular attention to the multifaceted positive effects of education. Specifically, higher levels of education are related to higher earnings, increased integration to labor market, better health status and nutrition for family and lower poverty (Haveman & Wolfe, 1984; Wolfe & Behrman, 1984; Tansel, 1997; Acemoglu & Angrist, 1999; Psacharopoulos & Patrinos, 2004; Belfield, 2008; Brunello & De Paola, 2014; World Bank, 2018). Furthermore, schooling is reported to generate non-pecuniary gains in terms of self-accomplishment, social interaction, better decision making process and attitudes such as risk-aversion, patience and motivation which influence economic choices (Oreopoulos & Salvanes, 2011; Brunello & De Paola, 2014). The benefits of education go far beyond individuals and society. From a broader perspective, the impact of education on the economic performance of countries is substantiated by the scholars via either school attainment or school enrollment rate in growth regressions (Barro, 1991; Mankiw et al., 1992; Levine & Renelt, 1992; Barro & Lee, 1993; Sala-i Martin et al., 2004).

When the aforementioned outcomes are considered in general, it is seen that early leaving from schooling is a social as well as an economic problem such that it is argued to yield reduced quality of education, increased social assistance expenditures and need to collect more taxes (Campbell, 2004; MEB, 2013). While the unfavorable effects of being out of school are evident in the studies specific to Türkiye and in the studies conducted for other countries, there emerges a substantial body of literature seeking to find out probable reasons of dropout. Empirical evidence suggests that the underlying reasons affecting both school dropout and participation in education are similar. The studies dealing with causes of school dropout tend to reveal multiple effects on the risk factors of early leaving, rather than being dependent on a single variable. In general, school dropout is reported to depend on demographic and socioeconomic factors as well as community-level influences such as family income, parental characteristics, sibship composition and size, household size, gender, age, location of residence and locative characteristics, religious and cultural factors. Related to this, much of the available literature on educational attainment and/or school dropout draws on the relationship between educational attainment and its determinants.

The proportion of children out of school is defined as the proportion of children who are of compulsory school age but have not enrolled in a school. According to Tunca et al., (2022), in Türkiye even though they are at the age of compulsory education, the number of those who are out of education increases after the age of 13 which corresponds to the highschool level of education as well as to the last four year part of whole compulsory education in Türkiye. For example, while 4.3% of 14-year-olds are not enrolled in school, this rate rises to 13.1% for 17-year-olds. To be more precise, according to a calculation made using age population data published by the Turkish Statistical Institute (TURKSTAT), approximately 82.902 children between the ages of 6 and 9, 82.929 children between the ages of 10 and 13, and 404.463 children between the ages of 14 and 17 are not in school in 2021-2022 academic year. In another report conducted in 2020-2021 for Türkiye, despite being in the age of compulsory education, it is observed that children are increasingly out of education (Tunca et al., 2022). For example, while 3.6% of 14-year-olds are not enrolled in school, this rate rises to 15.5% for 17-year-olds. Furthermore, as of the latest academic year, 100% enrollment in compulsory education levels in Türkiye has not been achieved yet (Tunca et al., 2022; amongothers).

Motivated with the fact that 100% participation in education has not been achieved, this study aims at estimating 5-17 years aged Turkish students' average expected school duration by using two latest available surveys conducted by TURKSTAT, namely Working Child Statistics (WCS) in 2019 and corresponding Household Labor Force Survey (HLFS) in a survival analysis. By doing so, the roles of socioeconomic status (e.g. education level of parents, employment status of parents, family composition etc.), demographics (e.g. gender, age etc.), and Türkiye's regions in determination of survival function will be estimated. Although much of the available literature has attempted to account for causes of school dropout in Türkiye, there is lack of evidence in accounting for the occurrence of school dropouts at certain grade levels and its potential influencers in Türkiye. Another issue that is addressed by the current study is right-censored nature of the outcome variable since the data consists of both group of individuals who dropped out and did not drop out (yet). In other words, we have information about the highest grade achieved by individuals who are no longer enrolled in schools whereas for those currently enrolled, this information is missing. Nevertheless, currently enrolled students are known to attain a grade at least current completion level. This factor should be considered when investigating school dropout or educational attainment. Therefore, by employing survival analysis this study offers some important insights into particular circumstances or characteristics that are instrumental in increasing or decreasing the probability of duration in education.

The rest of the essay is organized as follows: Section 3.2 reviews the literature, Section 3.3 introduces the Turkish education system, Section 3.4 describes and analyses the data, Section 3.5 outlines the methodology, Section 3.6 presents results from Survival Analysis, Section 3.7 discusses empirical findings and policy implications, and Section 3.8 concludes with a brief summary.

3.2. Literature Review

The literature on school dropout feeds on human capital theory which regards education as an investment (Mincer, 1958; Schultz, 1960; Becker, 1975). According to this theory, individuals weigh the future benefits of education -reflected in lifetime earnings associated with educational investments- against its direct and indirect costs. While direct costs are expenditures associated with schooling such as the cost of books, uniforms, school transportation and occasionally tuition, indirect costs represent opportunity costs related to schooling such as foregone workforce and earnings due to time devoted to school. Individuals choose to invest in education when the net present benefits of education outweigh the costs of attending school. In addition, although human capital theory does not consider the nonpecuniary benefits of education (Tansel, 1997) they might be influential for the decision of investment in education. Consequently, much of the literature on educational attainment and school dropout explores the relationship between educational attainment and its determinants.

Tansel (2002) conducted the first study examining the determinants of educational attainment in Türkiye. Using data from the 1994 Household Budget Survey (HBS) of the Turkish Statistical Institute (TURKSTAT), the study employed ordered probit models to analyze primary, middle, and high school attainment. The findings revealed that parental education, measured by the years of schooling completed by both the father and mother, and household permanent income, measured by total household expenditure per adult over age 15, were highly significant across all levels of schooling. The study also suggested that the influence of parents' education on their daughters' educational attainment was greater than on their sons', except when the mother had only completed primary school. Additionally, per adult household expenditure had a positive and significant effect on the educational attainment of both boys and girls at all levels. This implies that as household permanent income increases, the probability of higher educational attainment also increases, indicating that school attainment is a normal good (Tansel, 2002). The study also found that household income had a stronger impact on girls' education compared to boys' education.

This result was confirmed by other studies conducted in Türkiye, including Hisarcıklılar (2002), which analyzed the impact of familial characteristics on the educational attainments of boys and girls; Bakış et al. (2009), which aimed to explain primary and middle-level schooling; and Smiths and Hoşgör (2006), which investigated the effect of family background on educational participation. Hisarcıklılar (2002) noted that family income had a significant effect on girls' schooling but was insignificant for boys' schooling. Bakış et al. (2009) provided evidence of a positive and significant effect of household income per capita on high school attainment for both boys and girls, and on school attainment for girls. The study suggested that the relationship between education and income level weakened due to the beneficial effects of compulsory education, which was extended to the middle level in Türkiye in 1997. Similarly, Smiths and Hoşgör (2006) found that household income had a significantly positive effect on boys' participation in primary education and on participation in secondary education for both boys and girls. Regarding parents' occupational status, Tansel (2002) concluded that the father's self-employment had a significantly negative effect on boys' schooling at the middle and high school levels and on girls' middle school attainment. The study also indicated that residing in an urban area increased the probability of receiving higher education, with a larger effect for girls compared to boys. When analyzing educational attainment by region, the study found that the probability of educational attainment was higher in six regions compared to the Marmara Region, the most developed region of the country.

Göksel (2008) extended Tansel's (2002) work by controlling for the number of children in the family and the gender composition of children. Using data from the 1994 and 2002 Household Income and Consumption Survey of TURKSTAT, the study employed an ordered probit model to estimate the number of years of schooling for boys and girls separately. The results supported the significant effects of the number of children in the family, household expenditure, parental education, and the self-employment status of parents on boys' and girls' school attainment. Specifically, the number of children in the family and self-employment of parents had a significantly negative effect on school attainment, while household expenditure and parental education had a significantly positive effect on schooling levels. The study also found that age was insignificant in determining boys' school attainment but had a significantly negative effect on girls' schooling levels. The effect of sibling composition on school attainment differed by gender: having more brothers in the family had a significantly negative effect on girls' school attainment, while the number of girls in the household did not significantly affect boys' school attainment. This finding has been interpreted as reflecting gender role attitudes within families, where girls are generally expected to contribute more to housework activities, such as caring for siblings or the elderly, cleaning, and cooking, compared to their brothers. In other words, the opportunity cost of educating daughters is higher than that of educating sons (Tansel, 2002; Hisarcıklılar, 2002; Koç, 2008; Dayıoğlu & Kırdar & Tansel, 2009; among others). It is also possible that boys are expected to have higher returns on education compared to girls (Hisarcıklılar, 2002; Dayıoğlu et al., 2009; among others), or that in patriarchal societies, girls are expected to join their husband's family in the future, while boys are seen as a form of old-age security (Tansel, 2002; Smiths & Hoşgör, 2006; Dayıoğlu et al., 2009; among others).

Related studies, such as those by Dayıoğlu et al. (2009) and Koç (2008), examined the effects of sibship size, gender composition, and birth order on children's school enrollment in Türkiye. Dayıoğlu et al. (2009) argued that parental decisions regarding schooling and fertility are made jointly, meaning that the number of children in a family is not exogenous to children's schooling. To control for exogenous variation in family size, the authors used twins per birth as an instrumental variable, as this represents an unexpected increase in family size. Their study, based on data from the 1998 Turkish Demographic and Health Survey (TDHS) of Hacettepe University, employed a Two-Stage Least Squares (2SLS) regression and found that there was no causal effect of sibship size on school enrollment, and that birth order and sibling sex composition mattered more for poorer households. The effect of birth order on school enrollment was found to be nonlinear, with school enrollment first declining and then increasing as birth order increased. Koç (2008), using data from the 2006 Household Labor Force Survey (HLFS) of TURKSTAT, employed ordered probit models to define children's final grade attainment in four categories (no degree, primary school, middle school, high school) and controlled for parental characteristics, sibling characteristics, locative characteristics, regional dummies, and family income per child. The study found that parental education had positive effects on children's educational attainment, with a greater effect of the father's education on male children's education. Family income per child was found to positively affect girls' schooling but had no significant effect on boys' education. Additionally, parents' employment in agriculture had different effects based on the child's gender: having a mother working in agriculture increased the likelihood of sons' education, while having a father working in agriculture decreased daughters' likelihood of receiving education. Birth order effects also suggested that having siblings other than sisters reduced the probability of receiving higher education. Furthermore, children from urban families tended to have higher degrees of educational attainment compared to those from rural areas.

Aytaç and Rankin (2004) contributed to the literature by specifically examining the impact of modernity and traditionality on high school attainment in Türkiye. The study used the 1988 Turkish Family Structure Survey of the Government Statistical Institute in a logistic regression model to analyze high school graduation status among individuals aged 16 years or older. Modernity and traditionality were proxied by the father's characteristics, such as education level, employment status, having a religious marriage only, experience abroad, newspaper readership, and attitudes towards gender roles. The study included controls for region, urban residence, annual household income, number of children under age 13, and the mother's education and employment status. The results indicated significant differences in high school attainment between boys and girls. For example, girls were disadvantaged in terms of high school graduation if their parents had a religious marriage only, if their fathers believed in physical separation of sexes, and if they agreed with the idea that wives were only suitable for housework. The study also found that, compared to the least developed eastern region, a greater proportion of boys and girls graduated from high school in more developed regions, with the disparity being most pronounced for females. Furthermore, significant gender differences were observed in the impact of parental employment status and education levels on children's educational attainment. For boys, neither parent's employment status had a significant impact, whereas for girls, the mother's employment was significant. Similarly, parents' educational levels had a significant impact on adolescents' education, particularly for females. The study supported the findings of Tansel (2002) that both parents' educational attainment had a significantly positive effect on children's educational attainment, with a stronger effect for girls. Additionally, the study indicated that children in metropolitan regions were more likely to complete high school compared to those in urban or rural areas.

Tomul (2007) added to the literature by examining the link between family income and school participation. The study used data from the 2003 Household Budget Survey (HBS) of TURKSTAT to analyze the probability of school enrollment among individuals aged 18-23 across different income levels, categorized into five levels: low income, middle-low income, middle income, middle-high income, and high income. The findings indicated that family income had a significant effect on school participation for the country as a whole and for its regions. The Central Anatolian region experienced the highest effect of income increase on educational participation, while the Mediterranean region experienced the lowest. Similar to Tansel (2002), Tomul (2007, 2008) observed that income increases had a more significant effect on girls' participation in education than on boys' participation in Türkiye. In a related study investigating the determinants of school participation among individuals aged 15-18, Tomul (2008) reported that children's participation in education was significantly influenced by parental educational attainment and household income per capita. However, the impact of these variables varied: the father's education level had the most significant impact, whereas income level had the least impact. Studies by Hisarcıklılar (2002) and Smiths and Hoşgör (2006) also supported the major explanatory power of the father's educational level on school attainment for both boys and girls.

Kırdar (2009) focused on the factors influencing educational attainment in Türkiye, with a particular emphasis on ethnicity. The study used the mother's native language as a proxy for ethnicity (Kurds, Arabs, Turks, and Caucasians) and employed probit regression using data from the 1993 and 1998 Turkish Demographic and Health Surveys (TDHS) of Hacettepe University. To account for differences in school dropout at certain grade levels by ethnicity, a discrete time duration method was also employed. The study found that Kurdish and Arabic boys were significantly more likely to be unenrolled in school compared to their Turkish peers, whereas no significant difference was observed between Caucasian and Turkish boys. Similarly, Kurdish and Arabic girls were more likely to be unenrolled compared to their Turkish peers. However, when regional and familial characteristics were controlled, the difference in enrollment rates among ethnic groups vanished for boys but not for girls. The study also highlighted the importance of controlling for the timing of school dropout, as it found that location of residence and family characteristics fully explained differences in enrollment rates across ethnic groups for boys, but not disparities in timing of dropout. For girls, ethnic disparities persisted even after controlling for regional and familial characteristics.

Duman (2010) examined the factors contributing to differences in female educational attainment in Türkiye. Using data from the 2006 Household Income and Consumption Expenditure Survey of TURKSTAT, the study employed a censored ordered probit model and confirmed the normality of school attainment—i.e., as household income increased, so did the probability of girls' schooling. The study found that parental education had a significantly positive effect on girls' education, with the mother's educational attainment having a greater impact compared to the father's. Living in a rural area was found to have a significantly negative effect on female educational attainment, as were family size and composition, particularly the presence of small children, which confirmed the expectation that daughters are expected to care for younger siblings. The study also found that girls living in regions such as Central Anatolia, Black Sea, East Anatolia, and Southeast Anatolia were less likely to attain higher levels of education, whereas girls in the Mediterranean region were more likely to do so.

Gümüş and Chudgar (2016) explored school participation in Türkiye from the perspective of regional disparities and the factors contributing to these disparities. Using data from the 2008 Turkish Demographic and Health Survey (TDHS) of Hacettepe University, the study employed logistic regression to analyze school enrollment, with explanatory variables including children's demographic characteristics, household poverty, the education level of the household head, the mother's Turkish-speaking ability, household size, and the mother's attitudes towards traditional gender roles. The study found that a mother's ability to speak Turkish and the household head's education level were positively associated with school participation, while household poverty, being female, being older, having a more traditional mother, and large family size were negatively associated. Regional differences were significant, with girls in the North being more likely to be in education compared to boys, while in other regions, being female had a considerable negative impact on school attendance. The study also revealed that poverty had the lowest impact on school attendance in the East and the greatest impact in the North. Despite the East being the least economically developed region, social factors such as the education of the household head and gender role attitudes had a greater impact on schooling in this region.

Almış and Karakütük (2021) provided recent evidence on the determinants of secondary school exclusion in Türkiye by gender. Using data from the 2003, 2011, and 2016 Household Budget Surveys (HBS) of TURKSTAT, the study employed a binary logistic regression model to analyze the probability of being excluded from school. The study found that determinants of exclusion from school differed for girls and boys, and over the years as well. Disability status, health insurance, and parental education were significant factors for boys' exclusion from school, while rural/urban location, household size, disability status, and parental education were significant for girls' exclusion. The study also observed that secondary school boys and girls from low-income households were more likely to be excluded from school than their peers from high-income households in 2003 and 2016.

The studies presented thus far provide evidence related to the factors that influence school enrollment and dropout in Türkiye, and research conducted in various countries finds similar profiles of the characteristics of those who complete and those who drop out, despite differences in dropout and completion rates between countries. For example, in a multivariate regression analyis the study by Chernichovsky (1985) provided evidence related to Botswana. Household head's education level is reported to be the most significant determinant of child's schooling i.e., the more the household head is educated the more likely his/her children are enrolled in school. Similar to other research findings related to child's age, this study confirms older children's declining propensity to be enrolled in school compared to younger siblings. As opposed to the situation in Türkiye and other developing countries, girls are reported to be more likely to be enrolled in school compared to boys. Besides, in contrast to the famous quantity-quality trade off[15], the number of children aged between 7 and 14 years in a household seems to have a positive impact on schooling.

[15] Becker (1960) introduced quantity-quality model to explain the observed negative correlation between family income and family size. Families face a trade-off between having more children and having fewer but better-raised children. It is argued that income increase should increase both quantity and quality of children, but the quantity elasticity should be small compared to the quality elasticity. This implies that as family income increases, the cost of raising children becomes more expensive. As a result, the desired quantity of children falls.

Results related to rural vs. urban residence also corroborates findings from other studies that children who live in large villages are more likely to be enrolled in school than children living in rural areas.

Using 1980 Brazilian Population Census, the study by Psacharopoulos and Arriagada (1989) explored the impact of various economic, demographic, social and regional variables on the educational attainment of Brazilian children aged between 7 and 14 years in a logistic regression of child's being enrolled in school. Contrary to the findings in Türkiye and other developing countries, this study rejects discrimination of girls in terms of school enrollment in Brazil. Parents' education level appear to be one of the significant influencers of school enrollment, particularly mother's educational attainment is found to have a strong impact on child's school attainment.

Tansel (1997) conducted a study seeking to find the impact of parental education, gender, income, community child wages and cost of schooling represented by distance to nearest school on the demand for schooling at primary, middle and post-middle levels in two sub-Saharan African countries of Cote d'Ivoire and Ghana in which women attain much lower schooling levels than men. Similar to the studies conducted for Türkiye, this study concluded that in both Cote d'Ivoire and Ghana, the educational attainment of boys and girls is significantly correlated with their parents' level of education. In both male and female samples from both countries, the effect of father's education was larger than that of mother's education. In Ghana, both parents' education has a greater impact on their female children's education than on their male children's education, whereas in Cote d'Ivoire, the opposite is true. In both countries, the results indicate that the distance cost is a significant factor at each level of education. As an indirect measure of the cost of attending school, distance to schools has a negative effect on the educational attainment of male and female students in Cote d'Ivoire at the middle and high school levels. In Ghana, the effect of primary school distance was insignificant, while middle and secondary school distances were significant; in all samples, middle school distance coefficients were greater than secondary school distance coefficients. In Cote d'Ivoire, the opportunity cost of time spent in school as measured by community child wages was positive and significant, whereas in Ghana, it was insignificant. In the majority of samples from both countries, the effect of household income (proxied by per adult total expenditure) is confirmed to be positive and statistically significant.

The study by Dancer and Rammohan (2007) provides evidence related to Egypt, using 1997 Egypt Integrated Household Survey in a logistic regression. The results related to the influences from gender, rural vs. urban residence, parental characteristics, household income and age are consistent with the results from aforementioned studies. For example; being male, having additional post-school age female sibling and household income are significantly positively related to being currently enrolled in school. With regard to child's age, it is found that child's age has a positive significant effect while child's age in squared terms has a negative significant effect. This implies as a child gets older probability of dropping out of school increases but at a decreasing rate. In terms of parental characteristics, all levels of father's education affects children's school enrollment significantly and positively. It is reported that children whose fathers have more than highschool education are about 20% less likely to drop out of school than children whose fathers have no education. However, mother's education improves only the likelihood of girls' enrollment to school. Father's occupation is also reported to have an important role in the likelihood of a child going to school. Having a father who is employed causally, in farming, or unemployed has a significantly negative impact on the probability of a child being enrolled in school. In addition, rural residence is found to be significantly negatively related to probability of school enrollment.

In view of all that has been mentioned so far, studies of school dropout have attempted to account for contributors of a student's full disengagement from the education system by utilizing multinomial regression methods. These studies, although explain which factors are influential in determination of school dropout do not fully account for staying in school beyond a certain grade level or how a change in student's demographic or socioeconomic conditions will influence overall grade attainment. Motivated by this, the studies by Brown and Park (2002), Weybright et.al., (2017) and Boualaphet and Goto (2020) employed an approach that allows estimating duration of schooling for countries of China, South Africa and Lao PDR, respectively. In their study, Brown and Park (2002) analyzed data from China Poverty Research Association's 1997 survey of households in six poor provinces of China to examine the impact of individual, familial and school characteristics on duration of schooling by using Cox proportional hazard model. It is reported that conditional on having remained in school until the current time, the probability of poor and constraint children's dropout of primary school is three times higher than that of other children. Moreover, higher wealth (as proxied by household expenditure per capita), the number of siblings and father's years of education are reported to significantly reduce the likelihood of dropping out of school. In terms of gender influences, boys are found to be more likely to drop out of junior secondary school with respect to girls though there is no statistically significant difference in probability of boys and girls dropping out of primary school. As an evidence in South Africa, plot of hazard function by gender reveals that probability of dropping out of secondary school is higher for boys than girls (Weybright et.al.,2017). Furthermore, Cox regression results indicated that gender, living with mother and previously failing a grade significantly predicted dropout status. For instance, the hazard of dropout for girls is 28.2% lower compared to males; the hazard of dropout for an adolescent who lives with his/her mother is 29.1% lower than that of a peer who does not live with his/her mother and the hazard of dropout for a learner who previously repeated a grade is 35.7% greater than that of a learner who did not previously repeat a grade. As a recent evidence in a study by Boualaphet and Goto (2020) investigated determinants of dropouts from primary and lower secondary education in a South Asian country, namely Lao People's Democratic Republic by using Survival Analysis. In contrast to recently mentioned studies using survival analysis to account for school dropout, Cox regression model shows that girls are more likely to drop out of school than boys. Moreover, girls living in rural areas are more likely to early leave the education process than their peers. Furthermore, mother's level of education and existence of a school in the residence of living are identified as the factors that reduce the likelihood of dropout.

The research literature on school enrollment or school dropout has identified a number of factors related to family background (e.g., household income, parental education level, parental occupational status, the number and composition of siblings, household size etc.), demographics (e.g., gender, ethnicity, location of residence, community, etc.), individual attributes (e.g., disability, health, grade repetition, retention etc.) as important by using household surveys in a multinomial regression model framework. However, these studies are far from estimating children's duration in education and determinants of this duration. Put differently, it is important to estimate the certain grade levels at which school dropout occurs and how socioeconomic and demographic factors influence it. Although there are few examples of countries for which children's duration in education is studied, there is no such study conducted for Türkiye which is a developing country of young population. Therefore, this study aims at addressing Turkish children's expected school duration and its potential influencers by using the latest available Working Child Statistics and corresponding Household Labor Force Survey of TURKSTAT. To our knowledge, this is the first study to merge these two surveys, providing insights into Turkish children's school attainment in years and information related to their parents and Türkiye's regions at NUTS-1 and NUTS-2 statistical regional units.

3.3. Education System in Türkiye

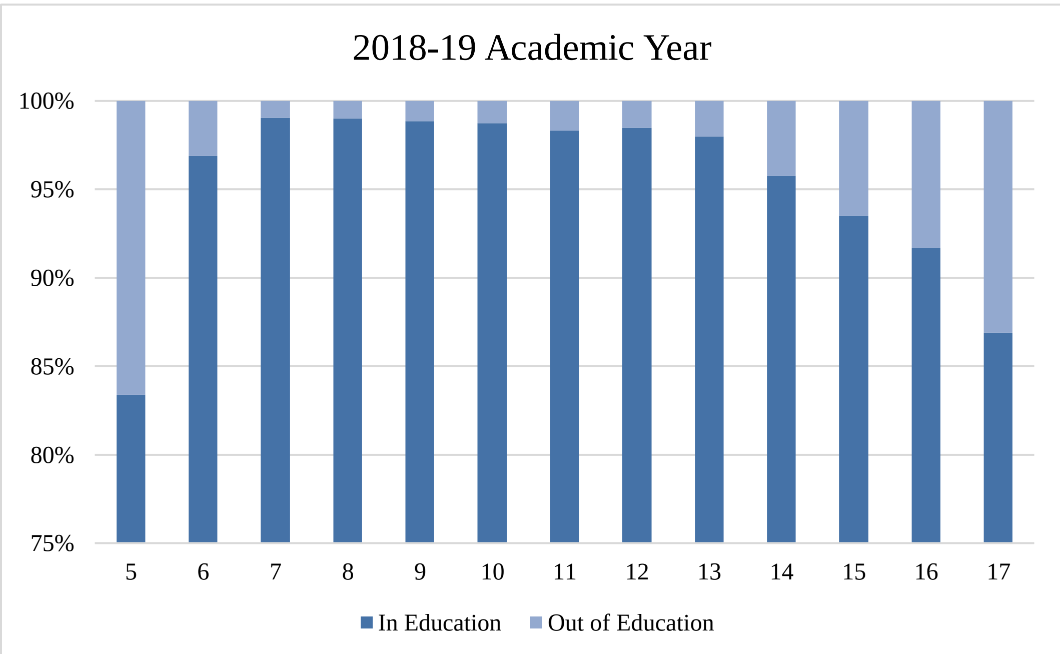
The educational structure in Türkiye comprises several levels, namely preschool education, primary education, secondary education, and higher education, which are provided by both public and private educational institutions. Public schools in Türkiye offer tuition-free education. Before the year 1997, the fundamental educational framework encompassed a five-year duration of primary education, succeeded by a three-year period of middle school. Since the year 1980, the educational policy in Türkiye has enforced obligatory attendance of elementary school, requiring individuals to complete a minimum of five years of education in order to meet the requirements. Law 4306, passed in 1997, sought to amalgamate primary and secondary education with the objective of modernizing the education system and expanding the duration of compulsory education from five to eight years.

In the year 2012, more educational changes were implemented to incorporate primary and secondary education, resulting in the establishment of a mandatory 12-year education system often known as the 4+4+4 schooling system. The 2012 change of the educational policy resulted in an expansion of the mandatory schooling duration from 8 to 12 years. This new structure encompassed four years dedicated to primary education, followed by four years of secondary education, and finally, four years of high school education. The last four years of mandatory education, equivalent to high school, are elective, allowing students the option to pursue distance learning which poses an obstacle to increase school participation.

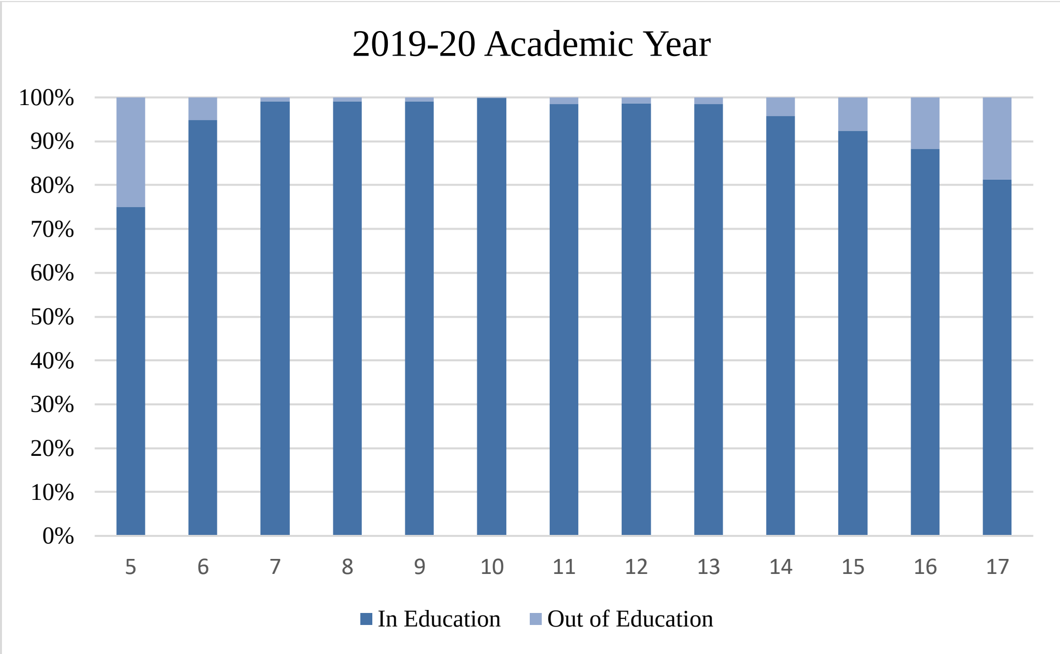
Despite the government's concerted efforts to increase school enrollment, this educational reform has presented challenges. It is worth mentioning that there has been a reduction in the age at which formal education begins, a rise in the number of religious educational institutions, a curriculum that prioritizes religious subjects over secular knowledge, and an increase in the rate of early school attrition. The deficiencies present in the Turkish education system have resulted in negative consequences for the overall quality of education and early dropout of school.

Panels (a) and (b) of Figure 3.1 present the ratio of students in education and out of education by ages in academic years of 2018-2019 and 2019-2020, respectively in Türkiye. In the academic year 2018-19, the enrollment rates within the compulsory education age range of 6-17 years have not reached 100%. When looking at the enrollment rates by age in panel (a) of Figure 3.1, it can be observed that there are children who do not have access to education across all age groups in 2018-19 academic year. Despite being within the compulsory education age, it is concerning that children increasingly drop out of education after the age of 12. 1.5% of children at the age of 12 are not registered in schools, and this rate increases to 13.1% for 17-year-olds. A similar pattern is observable in panel (b) of Figure 3.1 for 2019-20 academic year. Despite being of obligatory school age, children continue to drop out of school after the age of 12. 1.3% of children at the age of 12 are not registered in schools, and this rate increases to 18.8% for 17-year-olds.

Figure 3.1. The Ratio of Students in and out of Education by Ages in Education Years of 2018-2019 and 2019-2020 in Türkiye



(a)



(b)

Note: Calculated by net enrollment rate by single age data of MoNE[16]Education Indicators. “In Education” rate is the net enrollment rate, “Out of Education” rate is calculated by subtracting the net enrollment rate by age from 100.

3.4. Data and Descriptive Analysis

Working Child Statistics (WCS, thereafter) of TURKSTAT will be employed in this study. WCS was first conducted in 1994 with the aim of preparing a national database related to workplace conditions of working children while depicting respective distribution of them by sectors and social, demographic and economic characteristics related to working children. The rest of the surveys were conducted in order of 1999, 2006, 2012 and 2019. The universe of the survey consists of all households in all settlements of Türkiye and, at individual level, all household members in the age group 5-17. Since the survey was conducted together with Household Labor force survey (HLFS) it is possible to reach the information related to region/city settlements of the respondents by combining the two surveys based on household number for the year 2019. A two-stage, stratified cluster sampling method was used in the HLFS. In WCS survey, there are questions related to child’s educational status such as status of attending school, highest level of education completed, , grade and class if attending school, age at starting school, and non-attendance etc., and to child’s working status such as whether the child is working,

[16] MoNE is the abbreviation of Ministry of National Education in Türkiye.

economic activity, occupation, status in employment, working hours, location of workplace, monthly earning, causes of starting to work and working conditions etc., and to household chores such as cooking, washing, ironing, shopping, caring for siblings or ill household members, cleaning, repairing household items, etc., and to familial status such as education attainment of mother and father, employment status of mother and father, the sector of household the head etc. WCS micro dataset is considered to be useful for this study because the survey includes information related to each subject in the sense that their scholastic and socioeconomic status. The latest available WCS was conducted in 2019 together with HLFS of year 2019 are going to be employed in order to provide the most up to date information related to Turkish children's duration in education.

According to the information provided in WCS survey, it is possible to define two essential variables of survival data as EVENT and YEAR. EVENT is a binary variable and equals to 1 if the respondent has dropped out of school, and it takes 0 if he/she continues to education. The information related to a respondent's education continuation is available in EGITIM_M variable in the survey. EGITIM_M variable refers to the status of attending school and it has three categories as attending school (denoted by 1), not attending school (denoted by 2) and those who are under the age of compulsory education (denoted by 22). Those who are under the age of compulsory education are excluded because they are beyond the scope of study. YEAR is a discrete variable ranges from 0 to 14, and it represents the time (i.e. the number of years) it takes to drop out of school and calculated based on the information OKUL_BITEN and OKUL_AYRIL_SINIF variables in WCS survey. OKUL_BITEN variable refers to the highest level of education successfully completed by the respondent and it has five categories as no school completion (denoted by 0), primary school completed (denoted by 1), lower secondary school completed (denoted by 21), high school completed (denoted by 31) and vocational and technical (VAT, thereafter) high school completed (denoted by 32). OKUL_AYRIL_SINIF variable refers to the last class at which the respondent continued and it takes discrete values from 1 to 4, and the value of 9 representing the preparation class.

The explanatory variables encompass those factors implied by the body of literature related to school dropout, which are observable within the datasets of WCS and HFLS surveys. Accordingly, responses to the questions of gender, household size, age, working status and sector of the household reference person, educational status of mother and father, statistical regional unit at NUTS-2 level, working status of mother and father, employment status of the child, engagement in household chores and weekly actual hours spend in them, composition of siblings will be employed in the study. The final dataset includes 16 explanatory variables from 23502 observations in Türkiye. Table A in the Appendix provide the list of variables along with their explanations.

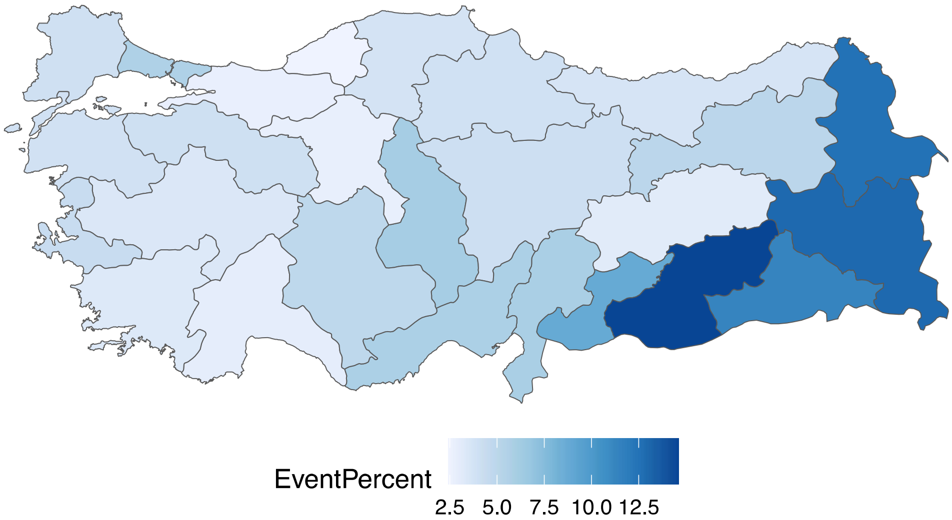
The dependent variable YEAR is the number of periods in education (measured in years) and it is right-censored. YEAR is considered to be complete when a person moves out of education; otherwise, the it is censored. The binary variable EVENT equals 1 if a person drop out of school (so is uncensored) and equals 0 (so is censored) otherwise. Table 3.1 shows summary statistics related to dependent variable as well as censoring variable. There are observations on 23502 individuals. Only 6% of years are observed to completion; the remaining years are censored. The mean period length, averaged over individuals with either complete or incomplete period, is 6.34 years.

Table 3.1. Summary Statistics for Dependent Variable

Variable Name	**Number of Observations**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
YEAR	23502	6.34	3.35	0	14
EVENT	23502	0.06	0.24	0	1

Figure 3.2 depicts cross-regional variation of school dropout in Türkiye. It is observed from the figure that school dropout rate increases as one moves to east and southeast regions of the country. The percentage of school dropout is the highest for TRC2 region (area colored as the darkest blue) being equal to 14.6% followed by TRB2 region being equal to 12.9%. TRA2 region records the third highest school dropout rate being equal to 12.5% followed by TRC3 region with 11.39%. The percentage of school dropout appears to be the lowest for TR81 region with a rate of 2.45% followed by 2.76% in TR42 and by 2.94% in TR61.

Figure 3.2. Percentage of School Dropout in 2019 by NUTS-2 Levels in Türkiye



Note: TRmaps package in R programme is used in development of the figure (Taştan,2021).

Figure 3.3 displays the distribution of YEAR variable which denotes the number of years that it takes to drop out of school. It is seen from the figure that most of the school dropout occurs at the year of 8 and then 9. 8 years of schooling corresponds to the end of middle school i.e. the second 4th of compulsory education process and the 9th year refers to either high school preparatory grade or the first grade of high school. Furthermore, there exist 35 observations whom attained 13 years of schooling and 1 observation whom attained 14 years of schooling. Additionally, the graph illustrates that there are several instances of students discontinuing their education at other grade levels as well.

Figure 3.3. Histogram of Number of Years to Drop out of School

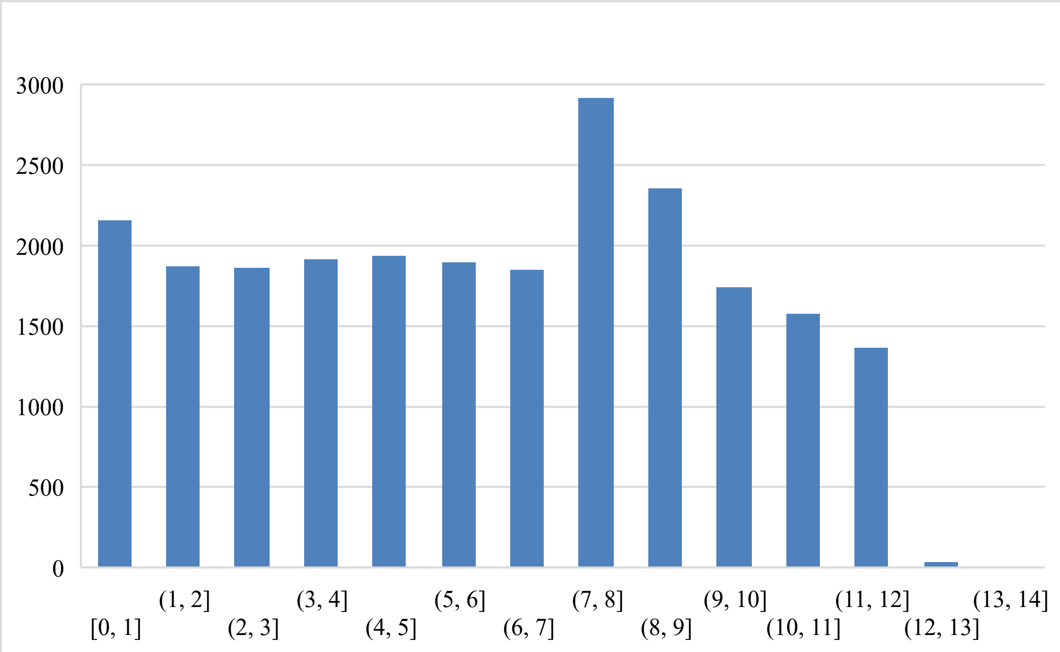


Figure 3.4 illustrates the distribution of household size, which is positively skewed. From the graph, it is evident that households with fewer than 8 people are more common, while more crowded families occur less frequently. The majority of families consist of 4 or 5 household members.

Figure 3.4. Histogram of Household Size

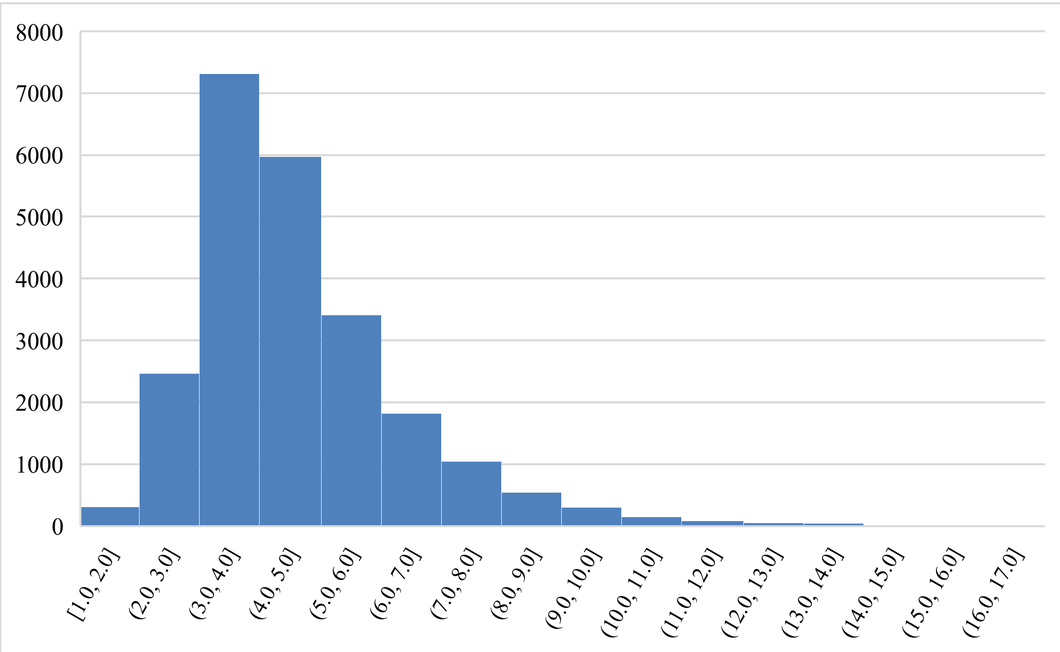
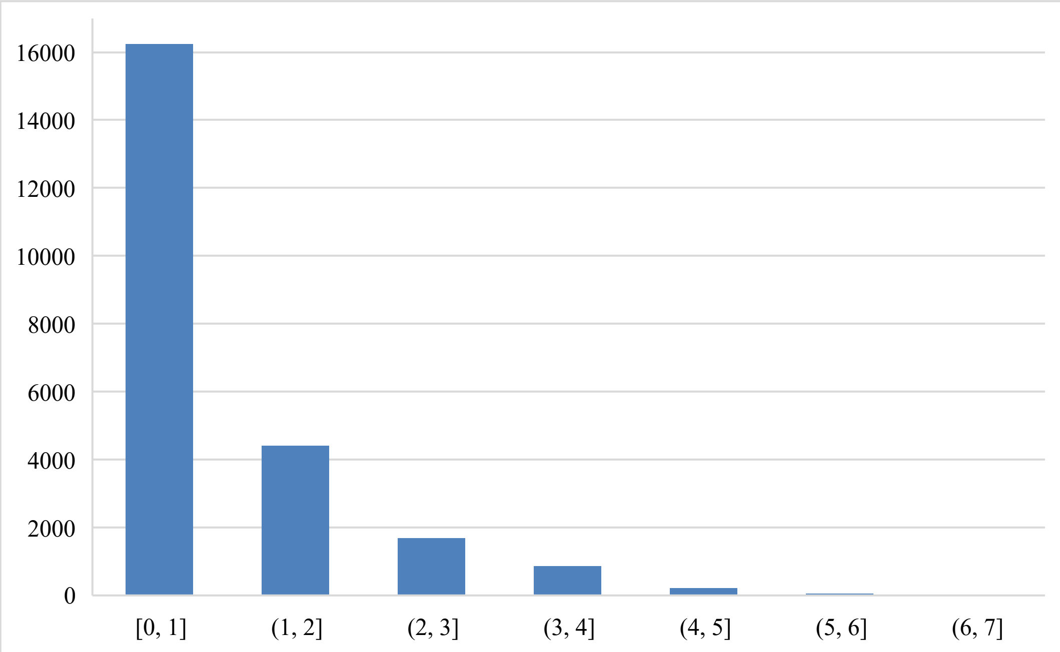


Figure 3.5. Histogram of Number of School Aged-siblings



The distribution of the number of siblings each child in the sample has at school age is depicted in Figure 3.5. The graph clearly illustrates that a majority of children possess either no siblings or only one sibling, but the occurrence of having two or more siblings is less frequent.

Table 3.2 provides information on the percentage of Turkish students in 2019 WCS sample based on their background characteristics. In 2019 WCS sample there are 23502 students of ages between 5-17. 6.25 % of these dropped out of school whereas 93.75 % had not experienced the event, i.e. they are censored. 4.8 % of the children in the sample is employed. The gender distribution is relatively balanced, with no significant differences between male and female students. The majority of the participants fall within the age range of 5 to 11 years, with the next largest group aged 12 to 14, and the smallest group consisting of individuals aged 15 to 17 years. According to the responses regarding educational and occupational background of parents, it appears that mothers of the participants have lower levels of educational attainment in comparison to fathers of the participants and mothers are more likely to be unemployed than fathers. The majority of students live with their mothers (98.14%) and fathers (90.6%) yet fathers are more likely to be absent from home with respect to mothers. Related to engagement with household chores, majority of the respondents do not work and contribute to housework (i.e. 50.2%) while 2,5 % of the children are engaged in both economic activity and housework. In particular; while the majority of students in the sample don't dedicate time to taking care of elderly, disabled, or ill family members in the household (94.41%), as well as caring for younger children in the household (77.1%), and performing daily housework (54.44%), there are still children who are involved in these types of tasks at home. the number of hours children spend on housework per week is primarily either under 2 hours (37.9%) or falls within the range of 3 to 7 hours (37%), with the next highest category being 8 to 14 hours (14.36%). Regarding composition of the household, majority of the participants do not have any siblings (29.4%), with the next most common one having at least one male sibling (26.1%), followed by having at least one female sibling (25.7%). Having both a male and a female sibling is the least common situation in the sample (18.8%).

Table 3.2. Total Number and Percentage of Turkish Students in the Sample of 2019 Working Child Statistics Survey based on Different Characteristics

	Total Number	Percentage
CINSIYET	**23502**	**100**
Male (M)	11948	50.84
Female (F)	11554	49.16
YAS_GRUP	**23502**	**100**
Aged 5-11(1)	11540	49.1
Aged 12-14 (2)	6086	25.9
Aged 15-17 (3)	5876	25
HHS_DURUM	**23502**	**100**
Employed (1)	17393	74
Unemployed (2)	1853	7.9
Not in labor force (3)	4256	18.1
ANNE_EGITIM	**23030**	**100**
Illiterate (1)	3441	14.94
Less than high school (2)	14277	61.99
High school (3)	1749	7.6
Vocational or technical high school (4)	1352	5.9
Higher education graduate (5)	2211	9.6
BABA_EGITIM	**21217**	**100**
Illiterate (1)	572	2.7
Less than high school (2)	13042	61.47
High school (3)	2169	10.22
Vocational or technical high school (4)	2201	10.37
Higher education graduate (5)	3233	15.24
ANNE_DURUM	**23030**	**100**
Employed (1)	7917	34.38
Unemployed (2)	1184	5.14
Not in labor force (3)	13929	60.48
BABA_DURUM	**21217**	**100**

Table 3.2.continued

	Total Number	Percentage
Employed (1)	17567	82.8
Unemployed (2)	1714	8.1
Not in labor force (3)	1936	9.1
COCUK_CALISAN	**23502**	**100**
Employed (1)	1127	4.8
Not employed (2)	22375	95.2
DURUM_COCUK	**23502**	**100**
Only engaged in economic activity (1)	540	2.3
Children engaged in economic activity and also children contributing to household chores (2)	587	2.5
Children contributing to household chores only (3)	10578	45
Children who are not working and also who do not contribute to housework (4)	11797	50.2
EVIS_DURUM1	**23502**	**100**
Generally (1)	2601	11.07
Sometimes (2)	8107	34.49
No time (3)	12794	54.44
EVIS_DURUM2	**23502**	**100**
Generally (1)	1127	4.8
Sometimes (2)	4256	18.1
No time (3)	18119	77.1
EVIS_DURUM3	**23502**	**100**
Generally (1)	210	0.9
Sometimes (2)	1104	4.7
No time (3)	22188	94.41
EVIS_SURE	**11165**	**100**
Never spend time (1)	96	0.9
Less than 2 hours (2)	4231	37.9
3 – 7 hours (3)	4136	37
8 – 14 hours (4)	1603	14.36
21 – 27 hours (5)	708	6.34
28 – 42 hours (6)	156	1.4
43 + hours (7)	235	2.1
SIBLINGS_COMP	**23502**	**100**
No Sibling (0)	6914	29.4
Male sibling (1)	6137	26.1
Female sibling (2)	6036	25.7
Both Male and Female Siblings (3)	4415	18.8

3.5. Empirical Methodology

Although the initial application of survival analysis originated in the field of medical research, these statistical techniques have found their place in economics and other social sciences. In this context, survival analysis[17] aligns with the objective of this study, which is to determine the expected school duration for Turkish students of compulsory school age. Additionally, the study aims to assess how various factors, including socioeconomic status (such as parents' education, employment status, household structure, and family income), demographics (including gender and age), and the geographic regions of Türkiye influence this duration. By doing so, present study takes into account the timing of dropouts and the peculiarity of the censored data on school dropout.

Survival analysis is a statistical approach that focuses on modeling time-to-event data, where the term "event" commonly denotes outcomes such as death or failure within the context of survival analysis literature. One unique feature of survival data is that there could be instances where event occurs either after or before the predefined survival period, meaning that they occur after the study has concluded. If this is the case, then these observations will be censored, and there is always the possibility of censoring in survival data. This situation requires particular methodological techniques for the analysis. The objective is to estimate the survival rate which is expressed in terms of survival function (i.e. the probability that an individual leaves longer than survival time, or in this study, the probability that individual continues to school). Let T denote the dependent variable i.e. duration. If the probability density function of T is denoted by $f(t)$ then the cumulative distribution function is as:

$$F(t) = P(T \leq t) = \int_0^t f(s)ds \qquad \textbf{(3.1)}$$

Survival function is the probability that the duration is at least t and it will be:

$$S(t) = 1 - F(t) = 1 - P(T \leq t) = P(T > t) \qquad \textbf{(3.2)}$$

Hazard function which is the probability of school dropout in the next short period of time, Δt, given that it lasted until time t will be:

$$h(t, \Delta t) = P(t \leq T \leq t + \Delta t \mid T > t) \qquad \textbf{(3.3)}$$

[17] Analysis of the data was conducted using the survival package in R programme (v3.2-7; Therneau, 2020).

The hazard rate is:

$$\lambda(t) = \frac{f(t)}{S(t)} \tag{3.4}$$

Survival function $S(t)$ and the hazard function $\lambda(t)$ can be estimated by a data based non-parametric approach namely Kaplan-Meier curve as:

$$\widehat{S(t)} = \prod_{j|t_j \leq t} \left(\frac{n_j - d_j}{n_j}\right) \tag{3.5}$$

$$\widehat{\lambda(T_j)} = \frac{d_j}{n_j} \tag{3.6}$$

respectively, and $t_j, j = 1, \ldots$ denotes times at which failure occurs; $n_j$is the number of students enrolled in school at time t_j and $d_j$is the number of dropouts at time t_j .

In addition to visual inspection, another way to find out whether survival probabilities are significantly different from each other is to utilize log-rank test. The log-rank test is a widely used statistical test employed to evaluate the null hypothesis of no difference in survival between two or more independent groups. Its statistic is distributed as chi-squared and calculated as:

$$\chi^2 = \sum \frac{(\sum O_{kt} - \sum E_{kt})^2}{\sum E_{kt}} \tag{3.7}$$

where ΣO_{kt} represents the sum of number of observed events in the k^{th} group over time (e.g., k=1,2) and ΣE_{kt} represents the sum of number of expected events in the k^{th} group over time.

In order to study the effects of various factors on school dropout, Cox Proportional Hazards model is employed. Given that the hazard rate in equation (3.4), and assuming there are p individuals observed, the hazard function is assumed to take the following form in the Cox model:

$$\lambda_i(t) = e^{x_i^T \beta} \lambda_0(t) \qquad i = 1, \ldots, p \tag{3.8}$$

where $x_i = (x_{i1}, x_{i2}, \dots, x_{ik})^T$is the vector of variables, $\beta = (\beta_1, \beta_2, \dots, \beta_k)^T$is the vector of regression coefficients, $\lambda_i(t)$is the hazard calculated for each individual, and $\lambda_0(t)$is the baseline hazard. The baseline hazard corresponds to the case where probability of death (or failure, in our case drop out of school) when all explanatory variables are 0.

3.6. Results

Panel (a) of Figure 3.6 illustrates Kaplan-Meier estimate of the survival function for whole sample. The compulsory education in Türkiye consists of three levels as primary (4 years), secondary (4 years) and upper secondary (4 years) education. The estimate shows large dropout rates at eighth and 12th years which correspond to the completion of each level of education and at ninth year which corresponds to the first year in highschool education. It also shows that chances for remaining in school decrease as the educational level gets higher. In panel (b), Kaplan-Meier estimate of the survival function for gender is presented. We can notice that although the probability of remaining in school for female children is quite close to that of male children, it is slightly larger for male children up to nine years of education. After 9 nine years of education, male children are more likely to drop out compared to their female peers. In addition, much wider confidence intervals are observed for female group implying there is more variability in that group compared to male group. It is also observed from the figure that for both genders, chances for remaining in school decrease as the educational level gets higher. Panel (c) displays the Kaplan-Meier estimate of the survival function related to the employment status of the child. The figure indicates that the likelihood of staying in education is greater for children who are not employed (i.e. children who are not employed are less likely to drop out of school), particularly evident after the primary years of education where the distinctions in these probabilities become pronounced, suggesting a survival benefit.

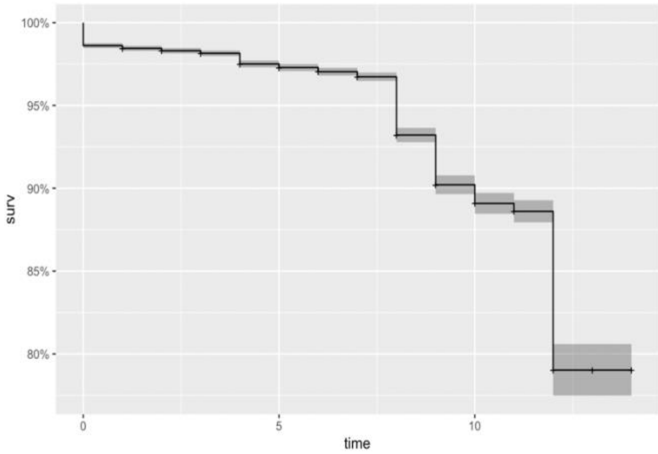
Panel (d) in Figure 3.6 represents Kaplan-Meier estimates of survival function for Türkiye's regions at NUTS-1 level. Although all the survival functions of Türkiye's regions seem to be nearing each other up to the end of primary education, differences in survival chances for staying in education become evident at the end of secondary education (i.e. eight years). Accordingly, the worst probability of remaining in education is pronounced for those from TRC region (southeast Anatolia), followed by TRA region (northeast Anatolia), and then TRB region (middle-east Anatolia). Subjects from TR1 region (Istanbul) have the fourth worst probability of staying in school followed by TR6 (Mediterranean), TR7 (middle Anatolia), TR2 (west Marmara) and TR3 (Aegean) regions. Students living in TR8 (west Black Sea), TR9 (East Black Sea) and TR4 (east Marmara) regions have the highest chances of survival in terms of continuing education. Overall, these results are consistent with the implications drawn from cross-regional variations in school dropout mapped in Figure 3.2.

Panel (e) of Figure 3.6 represents Kaplan-Meier estimates of survival function for siblings composition. Siblings composition variable is constructed such that it is equal to 0 if the subject has no siblings of school age at all, and 1 if the subject has at least one male sibling of school age, and 2 if the subject has at least one female sibling of school age, and 3 if the subject has at least one female and one male siblings of school age at home. It is clear from the figure that the probability of remaining in education decreases as the subject has both female and male siblings of school age at home. Moreover, the decrease in the survival rate is most prominent after secondary education (i.e. about eight years). After eight years of having remained in the education, the survival probability that a child continues to education is the least for ones who have at least one male sibling of school age at home, followed by the ones who have at least one female sibling of school age at home and the survival probability that a child continues to education is the highest for ones who have no sibling of school age at all.

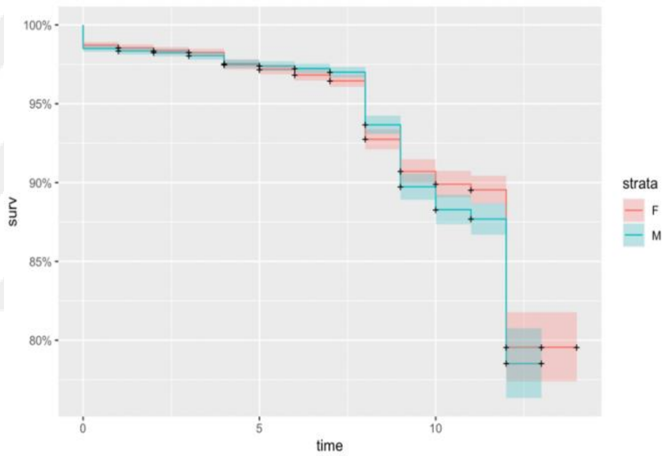
Panels (f) and (g) of Figure 3.6 represent Kaplan-Meier estimates of survival function for mother's and father's educational attainment, respectively. Both mother's and father's education are constructed such that it is equal to 1 for illiterate, and 2 for those having educational degree less than high school, and 3 for those having highschool degree and 4 for those having vocational and technical highschool degree and 5 for those who are higher education graduate. It is clear from the figures that survival probabilities for those who have illiterate parents are lower than survival probabilities of those who have educated parents. As parents' educational attainment increases survival chances improve suggesting a survival benefit.

Figure 3.6. Kaplan-Meier Estimates of Survival Function for Whole Sample and Different Groups

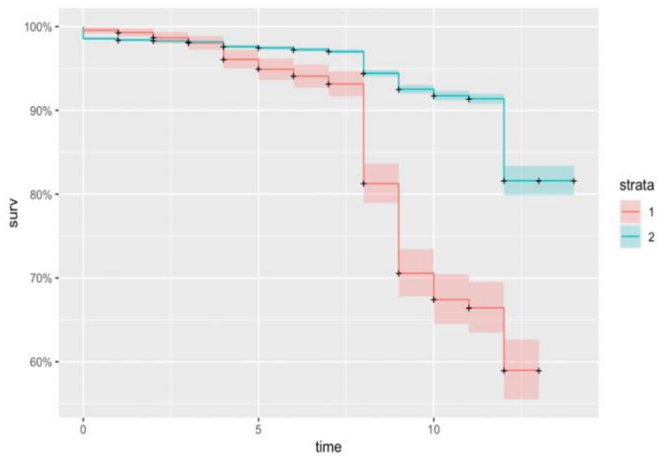
(a)



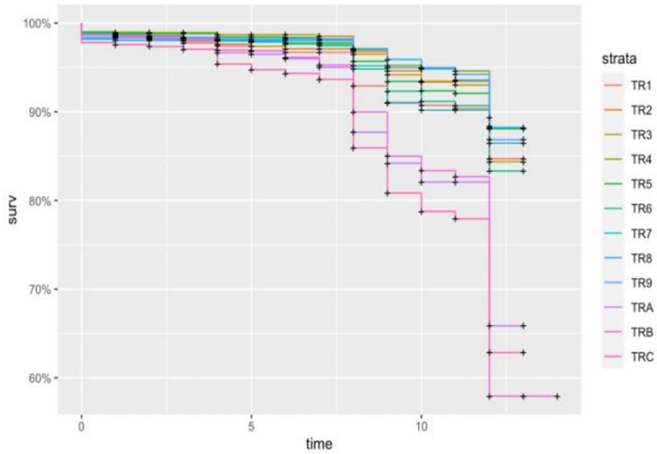
(b)



(c)



(d)



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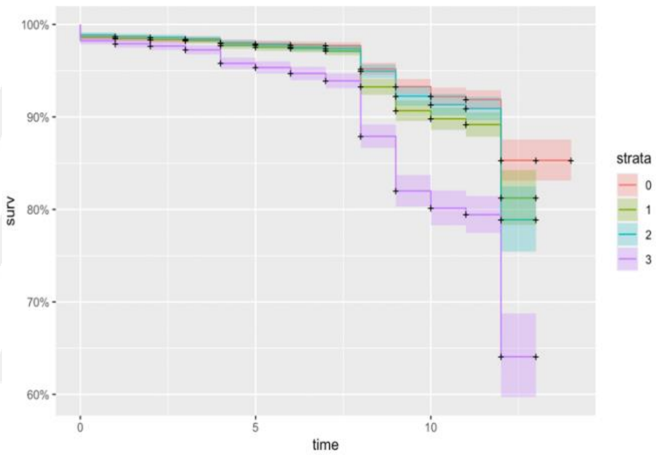
TRA
TRB
TRC

(e)



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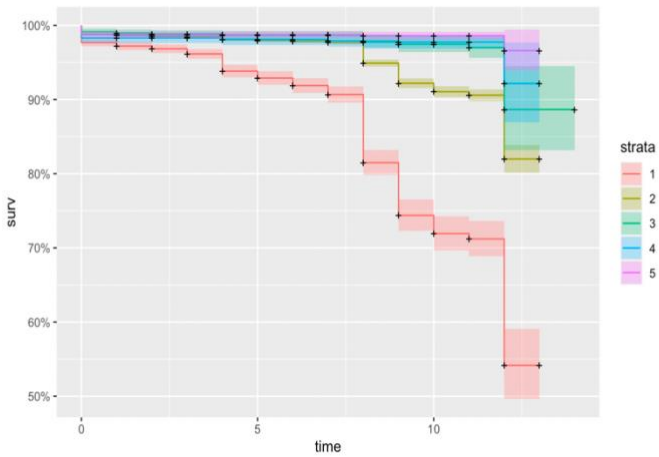

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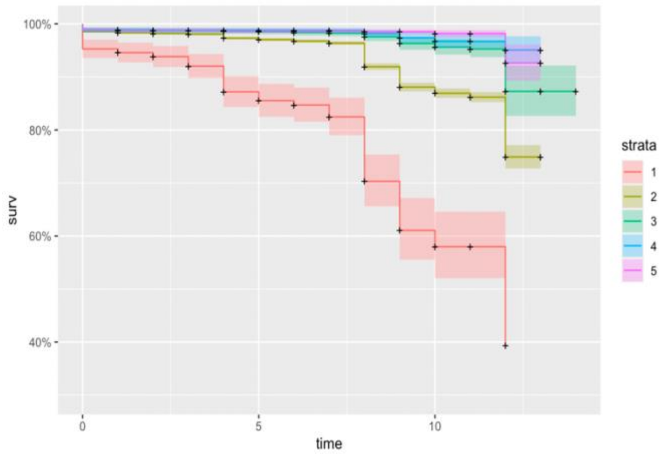


Note: In panel (b), F stands for female whereas M stands for male children. In panel (c), COCUK_CALISAN=1 indicates employed child whereas COCUK_CALISAN=2 indicates not employed child. In panel (d), TR1: Istanbul, TR2: West Marmara, TR3: Aegean, TR4: East Marmara, TR5:West Anatolia, TR6: Mediterranean, TR7: Middle Anatolia, TR8: West Black Sea, TR9: East Black Sea, TRA: Northeast Anatolia, TRB: Middle-east Anatolia, TRC: Southeast Anatolia. In panel (e) 0:No sibling, 1:Male sibling, 2: Female sibling, 3:Both siblings. In panels (f-g) 1:Illiterate, 2:Less than high school, 3: Highschool, 4: Vocational and Technical Highschool, 5:Higher education graduate.

In order to compare survival between groups within the sample, the Log Rank Test is employed. Table 3.3 briefly summarizes the results from log rank test based on different categories. It is observed from the table that p values related to education levels and employment status of mother and father, the region in which the subject resides, employment status of the subject, engagement with household chores, age group of the subject, weekly hours in household chores and composition of siblings are all significant indicating rejection of the null hypothesis stating that there is no difference in the survival probabilities of groups. So there are strong evidences in favor of significant differences between the survival probabilities of the considered groups except gender.

Table 3.3. Log Rank Test Results according to Different Categories

Category Name	Number of Observed	Number of Expected	χ^2 Statistic	P-value
CINSIYET				
Female (F)	709	725	0.7	0.4
Male (M)	760	744		
YAS_GRUP				
YAS_GRUP (1)	259	260		
YAS_GRUP (2)	271	418	95,8***	$< 2\times10^{-16}$
YAS_GRUP (3)	939	791		

Table 3.3.continued

Category Name	Number of Observed	Number of Expected	χ^2 Statistic	P-value
ANNE_EGITIM				
Illiterate (1)	575	211.5		
≤ Highschool (2)	740	914.1		
Highschool (3)	38	97.9	806***	$< 2\times10^{-16}$
VAT Highschool (4)	31	77.3		
Higher education Graduate (5)	31	114.1		
BABA_EGITIM				
Illiterate (1)	147	32.1		
≤Highschool (2)	994	829.3		
Highschool (3)	62	128.6	642***	$< 2\times10^{-16}$
VAT Highschool (4)	42	128.4		
Higher education Graduate (5)	56	182.6		
ANNE_DURUM				
Employed (1)	499	513.9		
Unemployed (2)	34	72.6	25.1***	4×10^{-6}
Not in labor force (3)	882	828.5		
BABA_DURUM				
Employed (1)	913	1064		
Unemployed (2)	132	101	141***	$< 2\times10^{-16}$
Not in labor force (3)	256	136		
COCUK_CALISAN				
Employed (1)	365	139	437***	$< 2\times10^{-16}$
Not Employed (2)	1104	1330		
EVIS_DURUM1				
Generally (1)	307	219		
Sometimes (2)	330	584	194***	$< 2\times10^{-16}$
No Time (3)	832	666		
EVIS_DURUM2				
Generally (1)	151	84.9		
Sometimes (2)	226	299.8	72***	2×10^{-16}
No Time (3)	1092	1084.4		
EVIS_DURUM3				
Generally (1)	46	19.1		
Sometimes (2)	77	80.9	40***	2×10^{-9}
No Time (3)	1346	1369.1		
EVIS_SURE				
EVIS_SURE (1)	2	6,08		
EVIS_SURE (2)	105	213.56		
EVIS_SURE (3)	186	257.46		
EVIS_SURE (4)	143	110.52	616***	$< 2\times10^{-16}$
EVIS_SURE (5)	97	51.02		
EVIS_SURE (6)	42	11.8		
EVIS_SURE (7)	78	15.35		
EVIS_SURE (8)	14	1.23		

Table 3.3.continued

Category Name	Number of Observed	Number of Expected	χ^2 Statistic	P-value
IBBS_2				
TR10	110	120.1		
TR21	22	35		
TR22	24	37.9		
TR31	37	54.2		
TR32	23	45.2		
TR33	24	43		
TR41	35	53.9		
TR42	24	56.9		
TR51	34	76.5		
TR52	65	81.5	592***	$< 2\times10^{-16}$
TR61	23	49.5		
TR62	63	67.9		
TR63	57	63.8		
TR71	47	53.1		
TR72	27	40.3		
TR81	7	18.8		
TR82	17	30.7		
TR83	32	51.4		
TR90	32	57.8		
TRA1	35	40.6		
TRA2	123	58.5		
TRB1	22	43.5		
TRB2	179	82.7		
TRC1	99	67.7		
TRC2	188	741		
TRC3	120	65.2		
SIBLINGS COMPOSITION				
Male sibling (1)	336	470	239***	$< 2\times10^{-16}$
Female sibling (2)	346	372		
Both siblings (3)	299	360		
No siblings at all (0)	488	268		

Note: 0.01, 0.05 and 0.1 significance levels are indicated by ***,**,*, respectively.

In order to determine the effects of covariates on survival (remaining in education) Cox Proportional Hazards Model is estimated and related results are briefly summarized in Table 3.4. Size of the household, number and composition of siblings, employment status of the child, the region from which the child is, gender and age group of the child, mother's and father's educational and occupational status, weekly hours spent on household chores by the child and the income earned in last month are controlled. Results from Cox Proportional Hazards model provide evidence in favor of significance of covariates as household size, the region, employment status of the child, child's age group, weekly hours spent on household chores by the child, employment and educational status of mother and father. This implication confirms the results of Log rank test which pointed out significant differences between the survival probabilities of the considered groups in categorical variables. More specifically, holding everything else constant, as household size increases by one person, the child will have 8.52% greater hazard of dropout. Similarly, children from TRB2 region -which includes cities of Van, Mus, Bitlis and Hakkari- have 57.93% and children from TRA2 region -which includes Kars, Ağrı, Iğdır and Ardahan cities- have 186.45% greater hazard of dropout compared to children from TR10 region[18] -which includes Istanbul city. In contrast, children from TR22 region -which includes Balıkesir and Çanakkale cities-, from TR32 region -which includes Denizli, Aydın and Muğla cities-, from TR33 region -which includes Manisa, Afyonkarahisar, Kütahya and Uşak cities-, from TR42 region -which includes Kocaeli, Sakarya, Düzce, Bolu and Yalova cities-, from TR61 -which includes Antalya, Isparta and Burdur cities-, from TR82 region -which includes Kastamonu, Çankırı and Sinop cities- and from TRB1 region -which includes Malatya, Elazığ, Bingöl and Tunceli cities- have 54.25% ; 50.26% ; 65.68% ; 48.61% ; 52.75% ; 69.93% and 65.81% respectively lower hazard rate than children from TR10 region.

Holding everything else constant, the estimated hazard ratio for children from age group 2, which includes those of 12-14 ages, to children from age group 1, which includes those of 5-11 ages, is equal to 0.6648. Related to child's engagement with household chores, children who are *sometimes* engaged with daily housework such as shopping for household, laundry-dishwashing, ironing, cooking, cleaning of household items etc., have 51.64% lower hazard compared to their peers who are *generally* engaged with daily housework at home. Similarly, as the child spends more time on houseworks i.e. more than 28 hours in a week, the hazard of school dropout increase exponentially compared to those who never commit such activities. Employment status of child appears to be significantly associated with school dropout: children who are employed in a job are at 68.87% greater risk of dropout compared to those who are not. Besides, the results from Table 3.4 substantiate significance of parental occupational status and educational attainment. Although unemployed mother appears to be insignificant, the estimated hazard ratio for

[18] In the Regression, TR10 region is the reference category of NUTS-2 regions of Türkiye.

children whose mothers are out of labor force to children whose mothers are employed is equal to 1.2456. In other words, a child whose mother is out of labor force has 24.56% more hazard compared to a peer whose mother is employed. Unlike the implication in mother's employment status, a child whose father is unemployed has 43.64% greater hazard than a child whose father is employed and the situation that the father is out of labor force appears to be insignificant. Finally, the model points out significance of parental educational attainment: both mother's and father's educational attainment appear to be associated with remaining in education, yet father's educational attainment is slightly more influential. Holding everything else constant; compared to a child whose mother is illiterate, a child whose mother has less than highschool degree has 42.86% lower hazard of dropout. These are 49.63 % and 69.09% lower hazards of dropout for a child whose mother has a general highschool and vocational/technical highschool degree with respect to a child with an illiterate mother. A child whose mother has higher education degree has 69.02% lower hazard of dropout than a child whose mother is illiterate. Similar inferences can be drawn for the influence of father's educational attainment: holding everything else constant; compared to a child whose father is illiterate, a child whose father has less than highschool degree has 42.96% lower hazard of dropout. These are 76.63 % and 89.03% lower hazards of dropout for a child whose father has a general highschool and vocational/technical highschool degree with respect to a child with an illiterate father. A child whose father has higher education degree has 76.14% lower hazard of dropout than a child whose father is illiterate.

Finally, the bottom panel of Table 3.4 provide summary statistics related to Cox Proportional Hazards regression. According to test statistics of Likelihood Ratio, Wald and Score tests the null hypothesis of survival is function of time can be rejected at 1% significance level, implying proposed covariates do have an influence on survival probability i.e. continuing education. In addition, concordance of the model is calculated to be 0.847 which is greater than 0.5 threshold implying that model is good at distinguishing survival times[19].

[19] The *c* index [concordance] is the proportion of all pairs of subjects whose survival time can be ordered such that the subject who experienced the event earlier has a higher predicted hazard or lower predicted survival probability.

Table 3.4. Estimation Results for the Cox Regression, Model (A)

Variable Name	Hazard Ratio	Inverse Hazard Ratio	P-value
HANE_BUYUKLUK	1.0852**	0.9215	0.0256
IBBS_2:TR21	0.6126	1.6324	0.1628
IBBS_2:TR22	0.4575*	2.1856	0.0748
IBBS_2:TR31	0.8297	1.2053	0.5044
IBBS_2:TR32	0.4974*	2.0103	0.0871
IBBS_2:TR33	0.3402**	2.9392	0.0326
IBBS_2:TR41	0.6912	1.4467	0.2683
IBBS_2:TR42	0.5139*	1.9457	0.0546
IBBS_2:TR51	0.8158	1.2257	0.5142
IBBS_2:TR52	1.0536	0.9491	0.8371
IBBS_2:TR61	0.4725**	2.1162	0.0430
IBBS_2:TR62	0.9446	1.0587	0.8184
IBBS_2:TR63	0.8790	1.1377	0.6034
IBBS_2:TR71	0.7183	1.3922	0.3014
IBBS_2:TR72	0.8723	1.1464	0.7219
IBBS_2:TR81	0.2598	3.8492	0.1073
IBBS_2:TR82	0.3007**	3.3252	0.0280
IBBS_2:TR83	1.0650	0.9390	0.8490
IBBS_2:TR90	1.1810	0.8468	0.6649
IBBS_2:TRA1	0.7126	1.4032	0.2874
IBBS_2:TRA2	2.8645***	0.3491	0.0006
IBBS_2:TRB1	0.3419**	2.9244	0.0199
IBBS_2:TRB2	1.5793**	0.6332	0.0372
IBBS_2:TRC1	1.4732	0.6788	0.1255
IBBS_2:TRC2	1.4384	0.6952	0.1042
IBBS_2:TRC3	1.3212	0.7569	0.2635
CINSIYET:M	1.0519	0.9507	0.6085
YAS_GRUP:2	0.6648**	1.5043	0.0463
YAS_GRUP:3	0.9497	1.0530	0.7883
EVIS_DURUM1_M:2	0.4836***	2.0677	3.37×10^{-9}
EVIS_DURUM1_M:3	0.7987	1.2521	0.3315
EVIS_DURUM2_M:2	1.1393	0.8777	0.4266
EVIS_DURUM2_M:3	0.9415	1.0622	0.7017
EVIS_DURUM3_M:2	0.6849	1.4601	0.1230
EVIS_DURUM3_M:3	0.7305	1.3689	0.1237
EVIS_SURE:2	1.8097	0.5526	0.4445
EVIS_SURE:3	1.9004	0.5262	0.4066
EVIS_SURE:4	2.1134	0.4732	0.3348
EVIS_SURE:5	2.4065	0.4155	0.2618
EVIS_SURE:6	6.7121**	0.1490	0.0153
EVIS_SURE:7	4.8862**	0.2047	0.0436
EVIS_SURE:8	8.2146**	0.1217	0.0102
COCUK_CALISAN:2	0.3113***	3.2127	$< 2\times10^{-16}$
ANNE_DURUM:2	0.7358	1.3591	0.2733

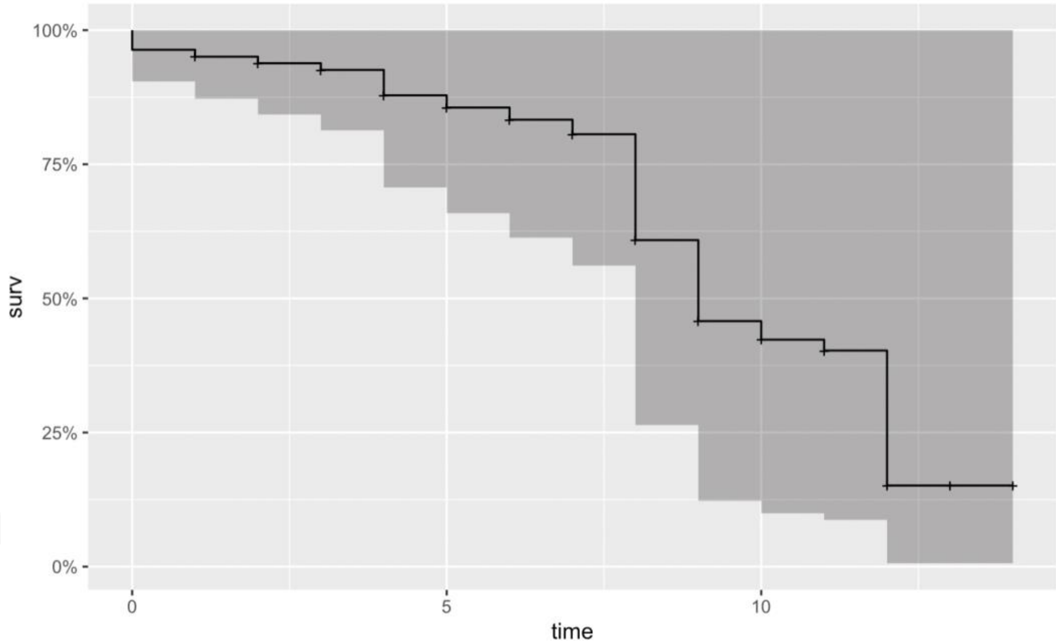
Table 3.4.continued

Variable Name	Hazard Ratio	Inverse Hazard Ratio	P-value
ANNE_DURUM:3	1.2456**	0.8029	0.0324
BABA_DURUM:2	1.4364***	0.6962	0.0066
BABA_DURUM:3	1.1200	0.8928	0.4237
ANNE_EGITIM:2	0.5714***	1.7500	3×10^{-6}
ANNE_EGITIM:3	0.5037**	1.9852	0.0298
ANNE_EGITIM:4	0.3091***	3.2350	0.0025
ANNE_EGITIM:5	0.3098**	3.2279	0.0253
BABA_EGITIM:2	0.5104***	1.9593	0.0002
BABA_EGITIM:3	0.2337***	4.2786	3.82×10^{-7}
BABA_EGITIM:4	0.1097***	9.1183	6.53×10^{-9}
BABA_EGITIM:5	0.2386***	4.1919	1.08×10^{-5}
SIBLINGS_COMP:1	0.8739	1.1442	0.3898
SIBLINGS_COMP:2	0.8223	1.2161	0.2111
SIBLINGS_COMP:3	1.1302	0.8848	0.5330
sibsize	1.0508	0.9517	0.4531
GELIR	1.0000	1.0000	0.1735
	Statistic		**P-value**
Concordance	0.847		
Likelihood Ratio Test	1048***		$< 2\times10^{-16}$
Wald Test	1135***		$< 2\times10^{-16}$
Score (log rank) Test	1682***		$< 2\times10^{-16}$

Note: Robust standard errors are employed. 0.01, 0.05 and 0.1 significance levels are indicated by ***,**,*, respectively.

Figure 3.7 briefly depicts the survival function predicted by Cox proportional hazards regression. The estimated survival function has a stair-step pattern. Accordingly, median duration in education is predicted to be 9 years. This means the probability of survival (not yet dropping out of school) past 9 years is 50%. Equivalently, 50% of compulsory school age children resulted in a school dropout at 9 years.

Figure 3.7. Survival Function Predicted by Cox Proportional Hazards Regression



The typical Cox model operates under the assumption that the hazard for an individual is the product of a baseline hazard function (which is not specified in the model) and an exponential function of a linear combination of covariates. In the context of Cox Regression, the proportional hazards assumption specifically states that the hazard ratio between any two individuals, based on their covariate values, remains constant over time. Table 3.5 briefly presents the results of proportional hazards assumption test proposed by Grambsch and Therneau (1994). The null hypothesis that covariate effect is constant (proportional) over time against the alternative as covariate effect changes over time is tested for each covariate individually and jointly in the test. From the output in Table 3.5, there exists significant evidence against proportional hazards: CINSIYET, YAS_GRUP, EVIS_DURUM2 and ANNE_EGITIM variables have significant test statistics at 5% level as well as the global test. Therefore, proportional hazards assumption is concluded not to hold for Cox Regression, Model A.

Table 3.5. Results of Proportional Hazards Assumption Test from Cox Regression, Model (A)

Variable Name	χ^2 Statistic	Degrees of Freedom	P-value
HANE_BUYUKLUK	2.84*	1	0.092
IBBS_2	31.253	25	0.181
CINSIYET	14.382***	1	0.00015
YAS_GRUP	12.596***	2	0.0018
EVIS_DURUM1	1.191	2	0.551
EVIS_DURUM2	6.454**	2	0.039
EVIS_DURUM3	3.852	2	0.1457
EVIS_SURE	7.412	7	0.3873
COCUK_CALISAN	2.117	1	0.145
ANNE_DURUM	4.489	2	0.106
BABA_DURUM	5.144	2	0.764
ANNE_EGITIM	9.852**	4	0.043
BABA_EGITIM	5.25	4	0.2626
SIBLINGS_COMP	6.465*	3	0.091
sibsize	0.319	1	0.5723
GELIR	0.367	1	0.545
GLOBAL	110.65***	60	5×10^{-5}

Note: 0.01, 0.05 and 0.1 significance levels are indicated by ***,**,*, respectively.

Because the variable of CINSIYET (gender) appears to be the one with the most severe violation of proportional hazards assumption in Model A, it is employed as the stratification variable in Model B. In the gender-stratified model, each level of the strata variable (i.e. Female, Male) is assumed to have a different baseline hazard function but the same coefficients for the other predictors in the model. Because the baseline hazard functions in different strata can vary over time differently, the ratio of hazards between individuals in different strata can vary over time. Estimation Results for gender-stratified Cox Regression are summarized in Table 3.6. It can be observed from the gender-stratified Cox regression that estimates and inferences related to significance of each variable as well as the model as a whole are quite similar to previous model without stratification.

Results from Cox Proportional Hazards model provide evidence in favor of significance of covariates as household size, the region, employment status of the child, child's age group, weekly hours spent on household chores by the child, employment and educational status of mother and father. This implication, again confirms the results of Log rank test which pointed out significant differences between the survival probabilities of the considered groups in categorical variables. More specifically, holding everything else constant, as household size increases by one person, the child will have 8.9% greater hazard of dropout. Likewise, children from TRB2 region -which includes cities of Van, Mus, Bitlis and Hakkari- have 58.6% and children from TRA2 region -which includes Kars, Ağrı, Iğdır and Ardahan cities- have 191% greater hazard of dropout compared to children from TR10 region[20] -which includes Istanbul city. In contrast, children from TR22 region -which includes Balıkesir and Çanakkale cities-, from TR32 region -which includes Denizli, Aydın and Muğla cities-, from TR33 region -which includes Manisa, Afyonkarahisar, Kütahya and Uşak cities-, from TR42 region -which includes Kocaeli, Sakarya, Düzce, Bolu and Yalova cities-, from TR61 -which includes Antalya, Isparta and Burdur cities-, from TR82 region -which includes Kastamonu, Çankırı and Sinop cities- and from TRB1 region -which includes Malatya, Elazığ, Bingöl and Tunceli cities- have 54.5% ; 51.27% ; 65.39% ; 49.06% ; 53% ; 69.66% and 66.31% respectively lower hazard rate than children from TR10 region.

Holding everything else constant, the estimated hazard ratio for children from age group 2, which includes those of 12-14 ages, to children from age group 1, which includes those of 5-11 ages, is equal to 0.3601. Related to child's engagement with household chores, children who are *sometimes* engaged with daily housework such as shopping for household, laundry-dishwashing, ironing, cooking, cleaning of household items etc., have 51.7% lower hazard compared to their peers who are *generally* engaged with daily housework at home. Similarly, as the child spends more time on houseworks i.e. more than 28 hours in a week, the hazard of school dropout increase exponentially compared to those who never commit such activities. Employment status of child appears to be significantly associated with school dropout: children who are employed in a job are at 69.07% greater risk of dropout compared to those who are not. Besides, the results from Table 3.6 substantiate significance of parental occupational status and educational attainment. Although unemployed mother appears to be insignificant, the estimated hazard ratio for children whose mothers are out of labor force to children whose mothers are employed is equal to 1.246. In other words, a child whose mother is out of labor force has 24.6% more hazard compared to a peer whose mother is employed. Unlike

[20] In the Regression, TR10 (Istanbul) region is the reference category of NUTS-2 regions of Türkiye.

the implication in mother's employment status, a child whose father is unemployed has 41.8% greater hazard than a child whose father is employed and the situation that the father is out of labor force appears to be insignificant. Finally, the model points out significance of parental educational attainment: both mother's and father's educational attainment appear to be associated with remaining in education, yet father's educational attainment is slightly more influential. Holding everything else constant; compared to a child whose mother is illiterate, a child whose mother has less than highschool degree has 42.7% lower hazard of dropout. These are 49.73 % and 69.34% lower hazards of dropout for a child whose mother has a general highschool and vocational/technical highschool degree with respect to a child with an illiterate mother. A child whose mother has higher education degree has 69.11% lower hazard of dropout than a child whose mother is illiterate. Similar inferences can be drawn for the influence of father's educational attainment: holding everything else constant; compared to a child whose father is illiterate, a child whose father has less than highschool degree has 48.35% lower hazard of dropout. These are 76.65 % and 88.9% lower hazards of dropout for a child whose father has a general highschool and vocational/technical highschool degree with respect to a child with an illiterate father. A child whose father has higher education degree has 75.81% lower hazard of dropout than a child whose father is illiterate.

Finally, the bottom panel of Table 3.6 provide summary statistics related to Cox Proportional Hazards regression. According to test statistics of Likelihood Ratio, Wald and Score tests the null hypothesis of survival is function of time can be rejected at 1% significance level, implying proposed covariates do have an influence on survival probability i.e. continuing education. In addition, concordance of the model is calculated to be 0,848 which is greater than 0.5 threshold implying that model is good at distinguishing survival times.

Table 3.6. Estimation Results for Gender-stratified Cox Regression, Model (B)

Variable Name	Hazard Ratio	Inverse Hazard Ratio	P-value
HANE_BUYUKLUK	1.0894**	0.9180	0.0179
IBBS_2:TR21	0.6059	1.6505	0.1561
IBBS_2:TR22	0.4550*	2.1977	0.0715
IBBS_2:TR31	0.8242	1.2133	0.4888
IBBS_2:TR32	0.4873*	2.0523	0.0794
IBBS_2:TR33	0.3461**	2.8890	0.0352
IBBS_2:TR41	0.6758	1.4797	0.2419

Table 3.6.continued

Variable Name	Hazard Ratio	Inverse Hazard Ratio	P-value
IBBS_2:TR42	0.5094*	1.9630	0.0502
IBBS_2:TR51	0.8131	1.2299	0.5077
IBBS_2:TR52	1.0560	0.9470	0.8294
IBBS_2:TR61	0.4700**	2.1275	0.0419
IBBS_2:TR62	0.9341	1.0706	0.7821
IBBS_2:TR63	0.8712	1.1478	0.5789
IBBS_2:TR71	0.7050	1.4185	0.2761
IBBS_2:TR72	0.8733	1.1450	0.7254
IBBS_2:TR81	0.2826	3.5388	0.1461
IBBS_2:TR82	0.3034**	3.2965	0.0281
IBBS_2:TR83	1.0610	0.9425	0.8572
IBBS_2:TR90	1.1810	0.8468	0.6616
IBBS_2:TRA1	0.7046	1.4193	0.2667
IBBS_2:TRA2	2.9088***	0.3438	0.0004
IBBS_2:TRB1	0.3369**	2.9682	0.0175
IBBS_2:TRB2	1.5859**	0.6306	0.0334
IBBS_2:TRC1	1.4644	0.6829	0.1310
IBBS_2:TRC2	1.3941	0.7173	0.1340
IBBS_2:TRC3	1.3202	0.7575	0.2598
YAS_GRUP:2	0.6399**	1.5627	0.0302
YAS_GRUP:3	0.9089	1.1002	0.6207
EVIS_DURUM1_M:2	0.4830***	2.0705	1.79×10^{-9}
EVIS_DURUM1_M:3	0.7764	1.2880	0.2813
EVIS_DURUM2_M:2	1.1370	0.8795	0.4270
EVIS_DURUM2_M:3	0.9511	1.0515	0.7464
EVIS_DURUM3_M:2	0.6985	1.4316	0.1383
EVIS_DURUM3_M:3	0.7396	1.3520	0.1338
EVIS_SURE:2	1.7802	0.5617	0.4564
EVIS_SURE:3	1.9185	0.5212	0.3986
EVIS_SURE:4	2.1328	0.4689	0.3277
EVIS_SURE:5	2.4278	0.4119	0.2557
EVIS_SURE:6	6.7202**	0.1488	0.0149
EVIS_SURE:7	4.8675**	0.2054	0.0436
EVIS_SURE:8	8.5025***	0.1176	0.0089
COCUK_CALISAN:2	0.3093***	3.2326	$< 2\times10^{-16}$
ANNE_DURUM:2	0.7490	1.3351	0.3036
ANNE_DURUM:3	1.2541**	0.7974	0.0263
ANNE_EGITIM:2	0.5728***	1.7457	3.04×10^{-6}
ANNE_EGITIM:3	0.5027**	1.9894	0.0300
ANNE_EGITIM:4	0.3066***	3.2613	0.0025
ANNE_EGITIM:5	0.3089**	3.2368	0.0250
BABA_DURUM:2	1.4182***	0.7051	0.0089
BABA_DURUM:3	1.1274	0.8870	0.3928
BABA_EGITIM:2	0.5165***	1.9360	0.0002

Table 3.6.continued

Variable Name	Hazard Ratio	Inverse Hazard Ratio	P-value
BABA_EGITIM:3	0.2335***	4.2828	3.63×10^{-7}
BABA_EGITIM:4	0.1110***	9.0095	6.78×10^{-9}
BABA_EGITIM:5	0.2419***	4.1341	1.16×10^{-5}
SIBLINGS_COMP:1	0.8767	1.1406	0.3977
SIBLINGS_COMP:2	0.8259	1.2108	0.2191
SIBLINGS_COMP:3	1.1216	0.8916	0.5543
sibsize	1.0503	0.9521	0.4482
GELIR	1.0000	1.0000	0.1590
	Statistic		**P-value**
Concordance	0.848		
Likelihood Ratio Test	1026***		$< 2\times10^{-16}$
Wald Test	1127***		$< 2\times10^{-16}$
Score (log rank) Test	1592***		$< 2\times10^{-16}$

Note: Robust standard errors are employed. 0.01, 0.05 and 0.1 significance levels are indicated by ***,**,*, respectively.

Table 3.7 presents results of proportional hazards test on gender-stratified Cox regression, Model (B). From the output in Table 3.7, there exists significant evidence against proportional hazards test: The test is statistically significant for covariates of YAS_GRUP, EVIS_DURUM2 and COCUK_CALISAN at 5% level as well as the global test. Therefore, proportional hazards assumption is concluded not to hold for gender-stratified Cox Regression, Model B.

Table 3.7. Results of Proportional Hazards Assumption Test from Cox Regression, Model (B)

Variable Name	χ^2 Statistic	Degrees of Freedom	P-value
HANE_BUYUKLUK	1.027	1	0.3108
IBBS_2	32.1177	25	0.1546
YAS_GRUP	12.3182***	2	0.0021
EVIS_DURUM1	5.6815*	2	0.0584
EVIS_DURUM2	6.9718**	2	0.0306
EVIS_DURUM3	2.7097	2	0.258
EVIS_SURE	11.368	7	0.1234
COCUK_CALISAN	4.9514**	1	0.0261
ANNE_DURUM	3.6463	2	0.1615
BABA_DURUM	8.2534*	4	0.0827
ANNE_EGITIM	4.6838*	2	0.0961
BABA_EGITIM	4.1615	4	0.3846
SIBLINGS_COMP	6.6564*	3	0.0837
sibsize	0.00201	1	0.9642
GELIR	0.8474	1	0.3573
GLOBAL	94.9368***	59	0.0021

Note: 0.01, 0.05 and 0.1 significance levels are indicated by ***,**,*, respectively.

Estimation Results for gender, age group and engagement with household chores-stratified Cox Regression (Model C) are summarized in Table 3.8. It can be observed from Model C that estimates and inferences related to significance of each variable except for TRA1 of IBBS-2 regions as well as the model as a whole are quite similar to previous models.

Results from Cox Proportional Hazards model provide evidence in favor of significance of covariates as household size, the region, employment status of the child, weekly hours spent on household chores by the child, employment and educational status of mother and father. This implication, once more confirms the results of Log rank test which pointed out significant differences between the survival probabilities of the considered groups in categorical variables. More specifically, holding everything else constant, as household size increases by one person, the child will have 8.34% greater hazard of dropout. Likewise, children from TRA2 region -which includes Kars, Ağrı, Iğdır and Ardahan cities- have 172.43% greater hazard of dropout compared to children from TR10 region[21] -which includes Istanbul city. In contrast, children from TR22 region -which includes Balıkesir and Çanakkale cities-, from TR32 region -which includes Denizli, Aydın and Muğla cities-, from TR33 region -which includes Manisa, Afyonkarahisar, Kütahya and Uşak cities-, from TR42 region -which includes Kocaeli, Sakarya, Düzce, Bolu and Yalova cities-, from TR61 -which includes Antalya, Isparta and Burdur cities-, from TR82 region -which includes Kastamonu, Çankırı and Sinop cities- and from TRB1 region -which includes Malatya, Elazığ, Bingöl and Tunceli cities- have 54.55% ; 54.24% ; 66.72% ; 49.77% ; 53.63% ; 70.47% and 68.86% respectively lower hazard rate than children from TR10 region.

Related to child's engagement with household chores, holding everything else constant, children who are *sometimes* engaged with daily housework such as shopping for household, laundry-dishwashing, ironing, cooking, cleaning of household items etc., have 50.94% lower hazard compared to their peers who are *generally* engaged with daily housework at home. Similarly, as the child spends more time on houseworks i.e. more than 28 hours in a week, the hazard of school dropout increase exponentially compared to those who never commit such activities. Employment status of child appears to be significantly associated with school

[21] In the Regression, TR10 (Istanbul) region is the reference category of NUTS-2 regions of Türkiye.

dropout: children who are not employed in a job are at 69.14% lower risk of dropout compared to those who are employed. Besides, the results from Table 3.8 significant evidence in favor of parental occupational status and educational attainment. Although unemployed mother appears to be insignificant, the estimated hazard ratio for children whose mothers are out of labor force to children whose mothers are employed is equal to 1.245. In other words, a child whose mother is out of labor force has 24.5% more hazard compared to a peer whose mother is employed. Unlike the implication in mother's employment status, a child whose father is unemployed has 37.3% greater hazard than a child whose father is employed and the situation that the father is out of labor force appears to be insignificant. Finally, the model points out significance of parental educational attainment: both mother's and father's educational attainment appear to be associated with remaining in education, yet father's educational attainment is slightly more influential. Holding everything else constant; compared to a child whose mother is illiterate, a child whose mother has less than highschool degree has 42.8% lower hazard of dropout. These are 50.18 % and 69% lower hazards of dropout for a child whose mother has a general highschool and vocational/technical highschool degree with respect to a child with an illiterate mother. A child whose mother has higher education degree has 69.56% lower hazard of dropout than a child whose mother is illiterate. Similar inferences can be drawn for the influence of father's educational attainment: holding everything else constant; compared to a child whose father is illiterate, a child whose father has less than highschool degree has 51.99% lower hazard of dropout. These are 77.5 % and 89.3% lower hazards of dropout for a child whose father has a general highschool and vocational/technical highschool degree with respect to a child with an illiterate father. A child whose father has higher education degree has 76.9% lower hazard of dropout than a child whose father is illiterate.

Finally, the bottom panel of Table 3.8 provide summary statistics related to model C. According to test statistics of Likelihood Ratio, Wald and Score tests the null hypothesis of survival is function of time can be rejected at 1% significance level, implying proposed covariates do have an influence on survival probability i.e. continuing education. In addition, concordance of the model is calculated to be 0.83 which is greater than 0.5 threshold implying that model is good at distinguishing survival times.

Table 3.8. Estimation Results for Gender, Age Group, Household chores -stratified Cox Regression, Model (C)

Variable Name	Hazard Ratio	Inverse Hazard Ratio	P-Value
HANE_BUYUKLUK	1.0834**	0.9230	0.0278
IBBS_2:TR21	0.5767	1.7342	0.1178
IBBS_2:TR22	0.4545*	2.2001	0.0638
IBBS_2:TR31	0.7301	1.3697	0.2640
IBBS_2:TR32	0.4576**	2.1852	0.0477
IBBS_2:TR33	0.3328**	3.0044	0.0299
IBBS_2:TR41	0.6807	1.4690	0.2453
IBBS_2:TR42	0.5023**	1.9907	0.0461
IBBS_2:TR51	0.7907	1.2646	0.4525
IBBS_2:TR52	0.9595	1.0422	0.8723
IBBS_2:TR61	0.4637**	2.1566	0.0367
IBBS_2:TR62	0.8531	1.1722	0.5135
IBBS_2:TR63	0.8772	1.1400	0.5960
IBBS_2:TR71	0.6636	1.5070	0.1952
IBBS_2:TR72	0.8493	1.1774	0.6664
IBBS_2:TR81	0.2648	3.7768	0.1035
IBBS_2:TR82	0.2953**	3.3859	0.0229
IBBS_2:TR83	1.0448	0.9571	0.8925
IBBS_2:TR90	1.2061	0.8292	0.6173
IBBS_2:TRA1	0.6387	1.5658	0.1598
IBBS_2:TRA2	2.7243***	0.3671	0.0013
IBBS_2:TRB1	0.3114**	3.2111	0.0118
IBBS_2:TRB2	1.3910	0.7189	0.1351
IBBS_2:TRC1	1.4757	0.6777	0.1130
IBBS_2:TRC2	1.3143	0.7609	0.2256
IBBS_2:TRC3	1.2025	0.8316	0.4697
EVIS_DURUM1_M:2	0.4906***	2.0385	5.76×10^{-9}
EVIS_DURUM1_M:3	0.8327	1.2009	0.4310
EVIS_DURUM3_M:2	0.7208	1.3873	0.1880
EVIS_DURUM3_M:3	0.7984	1.2525	0.2828
EVIS_SURE:2	1.6209	0.6170	0.5303
EVIS_SURE:3	1.8061	0.5537	0.4407
EVIS_SURE:4	2.0746	0.4820	0.3422
EVIS_SURE:5	2.3600	0.4237	0.2683
EVIS_SURE:6	6.5496**	0.1527	0.0162
EVIS_SURE:7	4.7338**	0.2112	0.0464
EVIS_SURE:8	9.2686***	0.1079	0.0068
COCUK_CALISAN:2	0.3086***	3.2400	$< 2\times10^{-6}$
ANNE_DURUM:2	0.7748	1.2907	0.3632
ANNE_DURUM:3	1.2446**	0.8035	0.0309
BABA_DURUM:2	1.3729**	0.7284	0.0175
BABA_DURUM:3	1.1259	0.8882	0.3963
ANNE_EGITIM:2	0.5720***	1.7483	2.29×10^{-6}

Table 3.8.continued

Variable Name	Hazard Ratio	Inverse Hazard Ratio	P-value
ANNE_EGITIM:3	0.4982**	2.0073	0.0268
ANNE_EGITIM:4	0.3099***	3.2274	0.0026
ANNE_EGITIM:5	0.3044**	3.2846	0.0230
BABA_EGITIM:2	0.4801***	2.0830	3.48×10^{-5}
BABA_EGITIM:3	0.2249***	4.4468	1.35×10^{-7}
BABA_EGITIM:4	0.1069***	9.3536	3.41×10^{-9}
BABA_EGITIM:5	0.2305***	4.3385	4.99×10^{-6}
SIBLINGS_COMP:1	0.8843	1.1309	0.4277
SIBLINGS_COMP:2	0.8568	1.1671	0.3254
SIBLINGS_COMP:3	1.1522	0.8679	0.4681
sibsize	1.0510	0.9515	0.4469
GELIR	1.0000	1.0000	0.1695
	Statistic		**P-Value**
Concordance	0,83		
Likelihood Ratio Test	880,1***		$< 2\times10^{-16}$
Wald Test	960,2***		$< 2\times10^{-16}$
Score (log rank) Test	1240***		$< 2\times10^{-16}$

Note: Robust standard errors are employed. 0.01, 0.05 and 0.1 significance levels are indicated by ***,**,*, respectively.

Table 3.9 presents results of proportional hazards test on gender-stratified Cox regression, Model (C). From the output in Table 3.9, evidence against proportional hazards test is weaker: The test is statistically significant for only the covariate of COCUK_CALISAN at 5% level. Based on the global test, we would conclude that the PH assumption is sufficiently satisfied for all variables. Nevertheless, it's important to acknowledge that, similar to all statistical hypothesis tests, the significance cutoff of 0.05 is arbitrary, and the conclusions drawn heavily depend on the sample size. Hence, in addition to the statistical test, it is prudent to inspect a visualization to evaluate the magnitude of any violation of the PH assumption.

Table 3.9. Results of Proportional Hazards Assumption Test from Gender, Age Group, Household chores- stratified Cox Regression, Model (C)

Variable Name	χ^2 Statistic	Degrees of Freedom	P-value
HANE_BUYUKLUK	1.339	1	0.247
IBBS_2	26.48	25	0.382
EVIS_DURUM1	1.3541	2	0.508
EVIS_DURUM3	3.9024	2	0.142
EVIS_SURE	11.65	7	0.113
COCUK_CALISAN	4.1994**	1	0.04
ANNE_DURUM	3.9558	2	0.138
BABA_DURUM	3.5587	2	0.169

Table 3.9.continued

Variable Name	χ^2 Statistic	Degrees of Freedom	P-value
ANNE_EGITIM	8.2758*	4	0.082
BABA_EGITIM	4.8898	4	0.299
SIBLINGS_COMP	6.0489	3	0.109
sibsize	0.0306	1	0.861
GELIR	0.9355	1	0.333
GLOBAL	73.3043	55	0.05

Note: 0.01, 0.05 and 0.1 significance levels are indicated by ***,**,*, respectively.

3.7. Discussion

The continued educational participation of children remains a significant issue in Türkiye. Despite governmental effort to increase enrollment rates, there is still a considerable number of school-aged children who are not engaged in primary or secondary education. The findings from this study offer a novel viewpoint, being the first to illuminate the duration aspect of school dropout in Türkiye.

While existing literature has largely focused on explaining the reasons for school dropout in Türkiye, there is a noticeable gap in understanding the occurrence of school dropouts at specific grade levels and their potential determinants. Hence, this study utilizes survival analysis to provide valuable insights into specific circumstances that play a pivotal role in either increasing or decreasing the likelihood of the duration of education.

Empirical findings of the study clarified that probability of not having dropout yet exhibited anticipated relationships with background characteristics. For example, household size appear to be a contributing factor to risk of school dropout in Türkiye. This could be due to utilization of income and resources by household members were notably influenced by the size of household and family structure. Parental education is another significant determinant of survival in terms of education: as mother’s and father’s educational attainment increases risk of school dropout decreases. This could stem from the fact that parents with higher level of education would have a greater understanding of the potential advantages of their children’s education. Consequently, their children were more likely to access educational resources and information as well as supervision and assistance with academic tasks. The adverse effect of child’s dedication to a full-time job or active involvement in household tasks on probability of survival in education is reasonable in the sense that occupancy in such activities would leave short time for school activities. Additionally, regional controls were significantly associated with the survival probability such that living in western regions of the country is more advantageous than living in eastern regions. This result is consistent with the fact that western region is more developed with respect to eastern region of Türkiye. Although the southeastern regions do not exhibit statistically significant differences from the most developed part of the country[22] (as indicated by p-values above conventional thresholds), the hazard ratios for TRC1, TRC2, and TRC3 remain substantial. These findings suggest notable increases in the hazard across all models considered, implying that, despite the lack of statistical significance, these regions may still experience meaningful risk differentials. Furthermore, results align closely with previously reached conclusions. There was an elevated risk of dropout for children from larger families (Duman, 2010; Gümüş & Chudgar, 2015), those with parents having lower levels of educational attainment (Psacharopoulos & Arriagada, 1989; Brown & Park, 2002; Tansel, 2002; Hisarcıklılar, 2002; Aytaç & Rankin, 2003; Smiths & Hoşgör, 2006; Dancer & Rammohan, 2007; Göksel, 2008; Koç, 2008; Tomul, 2008; Duman, 2010; Almış & Karakütük, 2021) or being unemployed, employed children, those dedicating considerable time to daily housework, and those living in the eastern regions of the country. Although significant impact of gender on school dropout probability is endorsed by numerous studies, present study finds such significance of gender related to the probability of survival (not yet dropping out of school).

3.8. Conclusion

Employing survival analysis, this study examined average expected school duration of Turkish children and its relationship with several factors by using the most recent Working Child Statistics survey conducted by Turkish Statistical Institute in 2019 and corresponding Household Labor Force Survey (HLFS). By undertaking this analysis, we aim to estimate the influence of various factors such as socioeconomic status parental education and occupational level, household composition, income, engagement with household chores, and demographics such as gender, age group and geographical regions within Türkiye on the determination of the survival function.

[22] It is the base category region which is TR10: Istanbul.

Kaplan-Meier estimate of survival function indicates that large school dropouts occur at eighth, ninth and 12th years which correspond to the end of middle school and highschool levels as well as the first year of highschool. This implies that there exists a disruption in the transition from middle school to highschool in Türkiye. Furthermore; in order to examine potential differences in survival times between different groups within the sample KM analysis is carried out for gender, employment status of the child, siblings composition and regions of Türkiye. It is observed that for both genders large dropouts occur at 8th, 9th and 12th years. Up to nine years, probability of remaining in education is similar for female and male children together with that female children are slightly more likely to stay in education during primary education, and that male children are slightly more likely to stay in education during middle school. After 9th year, male children are more likely to drop out. Regarding employment status of the child, KM analysis showed a large gap between employed and not employed children in terms of their remaining in education probabilities together with the observation that employed children are less likely to stay in education, as expected. Related to regional disparities in probability of remaining in education, all twelve regions of Türkiye are quite close to each other in terms of remaining in primary education together with that TRC (Southeast Anatolia) region is slightly worse in survival. Differences in survival probabilities based on regions become even more noticeable middle school onwards together with that TRA, TRB (Northeast and Middle east Anatolia, respectively) and TRC regions have the least survival probabilities. Concerning to the effects of siblings composition on survival chances of staying in education, the situation of having both female and male siblings is clearly the worst case with respect to having sister only and having brother only, and having no siblings at all. Besides, the discrepancy become evident with the large dropout in KM survival function estimate at 9th and 12th years.

In order to compare survival distributions of different groups within the sample, the Log Rank test is employed. The results of the Log Rank tests confirm the results derived graphically from the Kaplan-Meier estimates of the survival functions for child’s age group, mother’s educational attainment, father’s educational attainment, mother’s employment status, father’s employment status, employment status of the child, engagement with housework activities, caring for younger children or elderly in the household on a daily basis, weekly hours spent on such housework activities, NUTS-2 regions of Türkiye and composition of siblings: There exists significant evidence in favor of differences in survival probabilities of remaining in education for different groups.

To assess the impact of variables such as household size, siblings number and composition, child's employment status, region of residence, child's gender and age group, parental educational and occupational status, weekly hours spent on household chores by the child, and the income earned in the last month on the likelihood of remaining in education, the Cox Proportional Hazards Model is employed. The findings from the Cox Proportional Hazards model offer support for the significance of various factors, including household size, geographic region, the child's employment status, age group, the number of hours dedicated to household chores weekly by the child, and the employment and educational status of both parents.

Overall, the empirical findings from Kaplan-Meier analysis, Log rank test and Cox Proportional Hazards regression conform each other and suggest the importance of child’s employment status and active contribution to home duties, his/her age group, both parents’ educational attainment and their employment status as well as regional effects in determination of Turkish children’s likelihood of continuing education. Therefore, policies aim to mitigate adverse effects of insufficient socioeconomic endowments which contribute to exclusion of these children from education become crucial. Special consideration given to addressing regional disparities proves invaluable in endeavors to enhance school enrollment in Türkiye. Finally, implications drawn from current study may not be generalizable to other years yet it reflects recent stance of present situation. For future studies, other years together with the employment of different surveys would be suitable to check strength of results.

3.9. References

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3.10. Appendix

Table A. Variable List Considered in the Study

Variable code	Variable Description	Variable Type
EVENT	School Dropout (1), otherwise (0)	Categorical
YEAR	Time to Event (in years)	Discrete
CINSIYET	Gender: Male (M), Female (F)	Categorical
HANE_BUYUKLUK	Household Size	Discrete
YAS_GRUP	Age categories of children: Aged 5-11(1), Aged 12-14 (2), Aged 15-17 (3)	Categorical
HHS_DURUM	Working status of the household reference person: Employed (1), Unemployed (2), Not in labor force (3)	Categorical
ANNE_EGITIM	Educational status of Mother: Illiterate (1), Less than high school (2), High school (3), Vocational or technical high school (4), Higher education graduate (5)	Categorical
BABA_EGITIM	Educational status of Father: Illiterate (1), Less than high school (2), High school (3), Vocational or technical high school (4), Higher education graduate (5)	Categorical
ANNE_DURUM	Working status of Mother: Employed (1), Unemployed (2), Not in labor force (3)	Categorical
BABA_DURUM	Working status of Father: Employed (1), Unemployed (2), Not in labor force (3)	Categorical
IBBS_2	Statistical Regional Units in NUTS-2 level	Categorical
COCUK_CALISAN	Employment status (5-17 age group): Employed (1), Not employed (2)	Categorical

Table A.continued

Variable Code	Variable Description	Variable Type
DURUM_COCUK	Employment status of children in the 5-17 age group; Only engaged in economic activity (1), Children engaged in economic activity and also children contributing to household chores (2), Children contributing to household chores only (3), Children who are not working and also who do not contribute to housework (4)	Categorical
EVIS_DURUM1	Daily housework: Shopping for households, laundry-dishwashing, ironing, cooking, cleaning of household items etc: Generally (1), Sometimes (2), No time (3)	Categorical
EVIS_DURUM2	Caring for younger children in the household: Generally (1), Sometimes (2), No time (3)	Categorical
EVIS_DURUM3	Caring for elderly/disabled/ill person in the household: Generally (1), Sometimes (2), No time (3)	Categorical
EVIS_SURE	Weekly actual hours in household chores in reference week: Never spend time (1), Less than 2 hours (2), 3 – 7 (3), 8 – 14 (4), 21 – 27 (5), 28 – 42 (6), 43 + (7-8)	Categorical
sibsize	The number of siblings of school age	Discrete
SIBLINGS_COMP	Composition of siblings of school age: At least one male sibling (1), at least one female sibling (2), both male and female siblings (3), no sibling at all (0)	Categorical

4. THE MEDIUM-TERM EFFECTS OF EXTENDING COMPULSORY EDUCATION: EVIDENCE FROM 2012 EDUCATIONAL REFORM IN TÜRKİYE

4.1. Introduction

In light of technical, social, and economic transformations, countries are increasingly prioritizing the knowledge and skills possessed by individuals as they undertake economic and societal restructuring. The significance attributed to these human qualities, coupled with a continued upward trend in income and wealth, is fueling a heightened need for education in its most comprehensive form. Consequently, there exists an inherent inclination among individuals to pursue elevated levels of education, prompting governments to actively promote such pursuits.

Using a regression discontinuity design, this study examines the causal effect of Türkiye's recent education system change on high school and university completion rates, as well as on labor market outcomes such as employment status and earnings. The 2013-2022 waves of the Household Labor Force Survey (HLFS) conducted by the Turkish Statistical Institute (TURKSTAT) will be primarily employed in the research because these surveys provide the most recent and detailed information on education, specifically the last completed education level, employment status, and earnings of representative individuals. Specifically, this study aims to address the following questions: Does the extension of compulsory education from 8 to 12 years increase the total number of years of education attained, high school graduation rates (the intended effect), university graduation rates (the spillover effect), employment status, and earnings? Do these effects differ between genders?

With the recent education system change in 2012, the duration of compulsory education was increased from 8 to 12 years, comprising 3 successive 4-year periods corresponding to primary, secondary and high school education levels. Under the new system, students who were in the 8th grade during the 2011-12 school year were required to complete 12 years of schooling, whereas students who had completed the 8th grade or earlier were allowed to drop out. Consequently, if the school starting age is 6 years and this corresponds to the school year, individuals born after January 1998 would be affected by the law (i.e treated group), whereas individuals born before January 1998 would not.

As a result, individuals born after January 1998 are obliged to complete 12 years of education, while those born before January 1998 could drop out after completing 8 years. Using this cut-off point, a regression discontinuity design can be employed to estimate the causal effect of the policy on the number of years of schooling attained (i.e both the intended and spillover effect of the law). This is the first contribution of this study to the literature, as it investigates the effect of the 2012 compulsory schooling extension on intended grade level completion and on educational attainment beyond the intended level within a developing country context where young people constitute a significant portion of the population. Additionally, this study explores the impact of the compulsory education extension on individual career outcomes, including earnings and employment status, as well as high school and university graduation rates.

An overview of the literature on the effects of compulsory education extensions in Türkiye indicates that existing studies primarily focus on the consequences of the 1997 reform which extended compulsory education from 5 to 8 years and postponed religious middle school education to high school level, and the consequences of the 2012 reform which extended compulsory education from 8 to 12 years and moved religious education up to middle school level. The main difference between the two compulsory reforms relies in their gradation of education levels. 1997 reform mandated students to continue with 3 additional years of uninterrupted middle school education following 5 years of primary school. In other words, students were required to continue from primary to middle school without any distinction. The 2012 reform divided education into three stages: 4 years of primary school, 4 years of middle school, and 4 years of high school, allowing for transitions between these stages. Starting with middle school, students had the opportunity to pursue vocational or religious education at specialized schools. During the 1997 reform period, the availability of elective courses was quite restricted, with the curriculum primarily consisting of mandatory subjects. Although religious education was a compulsory subject, opportunities for students to engage in more in-depth religious studies as electives were limited. With the 2012 reform, religious education became more prominent among elective courses such as *The Quran* and *The Life of Prophet*, and there was an increased emphasis on schools that focused on religious education, such as Imam Hatip schools. Additionally, unlike the 1997 reform, the 2012 reform allowed for distance enrollment at the high school level, which could significantly influence high school graduation rates and the acquisition of necessary qualifications for the labor market as well as preparedness to pursue higher education. Therefore, incorporating higher education graduation and early career achievements in this study will help capture the spillover effect in addition to the intended effects of extending compulsory education in a developing country.

Studies related to the 1997 reform have investigated various aspects: the effect on mother's time spent in early childhood care, the ethnic gap in educational and labor market outcomes, time spent in religious activities, and voluntary work (Akar,2021); returns on schooling for women and men (Aydemir & Kırdar, 2017); earnings and labor force participation of men and women (Torun, 2018); school completion rates from 6^{th}- 8^{th} and 9^{th} -11^{th} grades (Kırdar, Dayıoğlu & Koç, 2016); schooling outcome and equality of this outcome between men and women, and urban versus rural areas (Kırdar, Dayıoğlu & Koç, 2016); and child labor (Dayıoğlu & Kırdar, 2022). However, evidence related to the 2012 reform is scarce. The study by Erten and Keskin (2019) investigates the effect of the recent reform on child labor and idleness, while the study by Yıldız (2022) examines the effect of the reform on high school grade completion. Currently, there is a lack of empirical evidence on the impact of recent educational reforms on higher education completion and early career outcomes, such as employment status and earnings. The effects of the 2012 reform encompass the impacts of all implemented changes. This study is the first to investigate both the intended effects of the 2012 compulsory schooling law in Türkiye, such as high school graduation rates, and the spillover effects, including university graduation, wages, employment status, and labor force participation. By systematically analyzing these outcomes, policymakers can better manage and optimize the education system to meet Türkiye's evolving educational needs, thereby enhancing the overall quality of education and its alignment with development goals.

The remainder of this essay is organized as follows: Section 4.2 reviews the literature on the effect of compulsory schooling laws on educational and labor market outcomes. Section 4.3 provides an overview of Turkish Compulsory Schooling Legislation. Data and methodology are explained in Section 4.4. Main results from Regression Discontinuity framework are presented in Section 4.5. Important findings are discussed in Section 4.6. Finally, Section 4.7 concludes with a brief summary.

4.2. Literature Review

The existing body of research on the effects of compulsory education laws on educational achievements in both developed and developing countries illustrates that such laws significantly enhance human capital development and labor market outcomes. Changes in the institutional features of schooling systems, serving as exogenous sources of variation, have enabled researchers to consistently estimate the returns to education. While the extensive literature on developed countries and the growing body of research on developing countries both underscore the positive impact of compulsory schooling laws on educational attainment, they offer differing conclusions regarding the returns from increased years of schooling.

Angrist and Krueger (1991) employed data from the 1960, 1970, and 1980 U.S. censuses in a difference-in-differences analysis to estimate the effects of compulsory school attendance on schooling and earnings. By exploiting variations in state compulsory attendance laws, their results suggest that individuals required to attend school until the legal dropout age tend to have higher wages due to increased education. This finding is corroborated by Acemoğlu and Angrist (2000), who used data from the 1960-1980 and 1950-1980 censuses to show that compulsory attendance and child labor laws significantly positively impact the number of completed years of schooling. Their 2SLS regression analysis estimates returns on an additional year of schooling at 7.5% and 7.3%, respectively.

Lleras-Muney (2002), employing 1960 census data, discovered that an additional year of compulsory schooling increases educational attainment by approximately 5% for both female and male 14-year-olds. Goldin and Katz (2008) corroborate the positive effects of compulsory education and child labor laws on overall educational attainment through a standard panel data model with state and year fixed effects, utilizing the 1960 U.S. census data.

More recently, Stephens and Yang (2014) confirmed that obligatory years of schooling result in a higher level of schooling attainment; however, the effect on the logarithm of weekly wages becomes statistically insignificant once region and year of birth are controlled in the specification. Clay, Lingwall, and Stephens (2021) extended previous studies in the US by providing evidence from earlier birth cohorts based on the 1940 census. Their first-stage estimates reaffirm the conclusion that obligatory years of schooling significantly increase completed years of schooling. Depending on the definition of the compulsory schooling law variable, the effect is reported to be nonlinear, indicating a substantial increase after nine or more years of requirement. Furthermore, they found a significantly positive return on education in quantile IV regressions, with lower quantiles showing larger returns than higher quantiles, suggesting that schooling increases wages more for those at the bottom of the earnings distribution relative to high wage earners.

The literature on the effect of compulsory schooling laws on educational attainment and income levels in North America is rich with empirical evidence from Canada. Oreopoulos (2006a) examined the overall impact of compulsory schooling and child labor laws in Canada between 1920 and 1990 by regressing average educational attainment levels on provincial compulsory schooling and child labor laws and a set of fixed effects. His results confirm findings similar to those observed in the US, showing that such laws effectively compel students to stay longer in school. Moreover, students with additional schooling are more likely to be bilingual, employed, and less likely to have low income or be unemployed and in manual labor. Conclusions regarding returns on schooling as a result of increased school attendance are drawn from the regression of earnings on predicted school attainment from the first stage. It is reported that students who were mandated to complete an additional year of education observed an average rise in their yearly earnings of approximately 12% (Oreopoulos, 2006a). Furthermore, a cross-country study by Oreopoulos (2006b) compares evidence related to the US and Canada with that of the United Kingdom and Northern Ireland. Using birth cohorts from 1901 to 1961 aged 25-64 in 1950-2000 censuses for the US, 1911-1961 birth cohorts aged 25-64 in 1971-2001 censuses for Canada, and 1921-1951 birth cohorts aged 32-64 in 1983-1998 General Household Surveys (GHS) for the UK and Britain, this study reports a significantly positive effect of a minimum obligatory school-leaving age of 14 on the number of years of schooling for the US and Canada and on the age left full-time education for the UK and Britain. Moreover, the effect is reported to be stronger in the UK and Britain than in North American countries. The logarithm of earnings is found to be strongly associated with minimum school-leaving age requirements for all countries considered in the study (Oreopoulos, 2006b).

Shifting to the opposite shore of the Atlantic, empirical research from the United Kingdom and other European countries illuminates the experiences with compulsory schooling policies in developed countries. For instance, the study by Harmon and Walker (1995) explores the impact of raising the school-leaving age from 14 to 15 in 1947 and a further increase from 15 to 16 in 1973 in the UK by pooling nine Family Expenditure Surveys between 1978 and 1986. The part of the study which estimated the return on years of schooling employs OLS and reports about a 6 percent return, which is quite smaller than the 15.25 percent estimated by 2SLS involving the two legislation changes as instruments for the years of schooling in the first-stage equation. Moreover, according to the first-stage results and ordered probit estimations, both of the legislation changes that increased the school-leaving age have a significantly positive effect on completed schooling in the UK (Harmon & Walker, 1995).

The paper by Devereux and Hart (2010) addresses the return on compulsory schooling by replicating the study of Oreopoulos (2006b). Employing the same survey for the same birth cohorts (i.e., General Household Survey between 1975 and 2001) as well as a new dataset, specifically the New Earnings Survey Panel Dataset (NESPD), spanning the same period of time in OLS and 2SLS regressions in an RDD framework, it is reported that the impact of the 1947 law, which increased the minimum school-leaving age from 14 to 15 in the UK, is to increase the average school-leaving age by 0.47 year for men and 0.55 year for women. This is verified with NESPD data such that the same impact is reported as 0.4 year for men and 0.5 year for women. Moreover, these impacts are reported to be strongly significant. The 2SLS estimate of return to schooling for men is found to be about 5% for hourly wages and about 6% for weekly earnings and statistically significant. However, the same is estimated as very close to 0 and statistically insignificant for the female sample. It is important to note that these estimates are substantially lower than the estimates reported by Oreopoulos (2006b). Therefore, in a corrigendum by

Oreopoulos (2008), it is found that the first-stage estimates of the number of years of schooling remain the same yet returns to schooling estimates are around 7% instead of 15%.

The study of Grenet (2011) extends previous RDD studies attempting to evaluate compulsory schooling laws in that it compares the 1972 UK compulsory education expansion to age 16 to that of the 1967 French reform. Employing 1944-1962 birth cohorts aged 25-60 in 1990-2002 French Enquete Emploi Surveys this study concludes that raising the minimum school-leaving age to 16 increased the average number of years of education by 0.272 years for females and 0.264 years for males. Similarly, employing 1948-1967 birth cohorts aged 25-60 in 1993-2006 Quarterly Labor Force Surveys in England and Wales, it is concluded that raising the minimum school-leaving age to 16 increased the average number of years of education by 0.309 years for females and 0.267 years for males. According to the same study, although the 1967 French reform and the 1972 UK have comparable effects on education, they have profoundly different impacts on wages: Both reduced form RDD estimates and the 2SLS results imply that reform’s impact on the hourly wages in the French case is not statistically different from 0 whereas the estimates for England and Wales are found to be significantly positive for both females and males. In order to assess the impact of the 1999 reform which extended vocational education by one year in Poland, on hourly wage of people who graduated from vocational schools, Liwinski (2020) follows a regression discontinuity analysis for the years 2001-16 by treating those born in and after 1986. The study finds that those who are compelled to study one more year are about to earn 3.3% more than those who are not subject to the new regulation and this result is stated to represent the causal effect of having 0.25 years of more education. However, it is worth noting that the effect is found to be 2.9% and weakly significant for males whereas it is equal to 2.1% and insignificant for females.

The previously confirmed results of increased overall educational attainment and positive return on schooling as measured by exposure to increased compulsory education are likewise relevant to the case of Swedish 1950 reform which extended compulsory education from 7 years to 8 or 9 years depending on the municipality (Meghir & Palme, 2005). Using the propensity score matching method, it is reported that the reform implied an increase in overall educational attainment of 0.27 year for males and a 0.22 year increase for females, as well as a significant increase in the logarithm of pre-tax earnings by 4.4%. In another study related to 12 European countries; Brunello, Fort, and Weber (2009) evaluate how the increase of minimum school-leaving age in different EU countries affects earnings distribution by treating these countries as regions of a country and their school reforms as episodes of a broader European trend. Using quantile regression in a 2SLS estimation in a difference in differences framework, they find evidence in favor of a positive significant effect of compulsory schooling extensions on years of education as well as earnings as one move from the lowest to the highest quantile of the ability distribution.

The exogenous variation stemmed from compulsory schooling laws has been used in the empirical literature pertaining to other European countries as well. For example, the study by Pischke and Von Wachter (2008) examines the effect of raising compulsory schooling from 8th grade to 9th grade in different states of Germany on years of education and wages by employing two German surveys in a difference in differences analysis and concludes that the introduction of 9th grade led from 0.19 to 0.28 years increase among different study tracks in the German education system. Such an impact of the same law for the same time period considered is verified as significant and positive by another study conducted for Germany as 0.6 years increase (Kemptner et.al., 2011). Related to evidence of earnings, the former study is far from reporting significant returns on education for Germany: the instrumental variables estimate of the logarithm of wages on the dummy variable indicating whether the state had introduced compulsory 9th grade is not necessarily different from 0, besides the effect is established to be valid across another large survey conducted for Germany (Pischke & Von Wachter, 2008). The previously established result of a 0 return to schooling, observed in the contexts of France and Germany, has also been found to be applicable in the case of the Netherlands. Oosterbeek and Webbink (2007) assess the effects of the extension of vocational training programs in the Netherlands from 3 to 4 years in 1975 in a difference in differences analysis and report that there is no significant effect on return to schooling as measured by exposure to increased compulsory education.

Motivated to better understand the role of compulsory schooling laws in the process of educational and labor market outcomes, a collection of researches are conducted in developing countries as well. These studies include Clark and Hsieh (2000), Spohr (2003), Tsai, Liu, Chou, and Thornton (2009), and Zhang (2020) on Taiwan; Shidiqi and Choi (2023) on Indonesia; Elsayed (2019) on Egypt; Fang, Eggleston, Rizzo, Rozelle, and Zeckhauser (2012) on China; Korwatanasakul (2023) on Thailand; Mocan (2014), Aydemir and Kırdar (2017), Erten and Keskin (2019), Kırdar, Dayıoğlu, and Koç (2016), Torun (2018), Akar (2021), and Yıldız (2022) on Türkiye.

The 1968 Taiwanese reform which extended compulsory schooling to 9 years from 6 has been found to lead significant increase in the educational attainment of birth cohorts affected by the law. Clark and Hsieh (2000) employ 2SLS regression in a difference in differences analysis by treating those who are aged 12 in 1968 as the treatment group. It is reported that the treatment group's probability of attending junior high school increased by 25%-40% and their probability of attending high school increased by 8%-13% with respect to the control cohort. There is no evidence in favor of the policy-affected group's probability of attending beyond high school level found in the same study. In order to evaluate whether the increased level of schooling induced by the expansion in compulsory education affected labor market outcomes such as labor market participation and wages, estimated schooling values from the first stage are employed as an instrumental variable in the second stage, and it is found that return on additional schooling as measured by the logarithm of monthly income is significantly positive and is about 3%-4%. Finally, no significant evidence in favor of any difference in labor force participation rate between policy-affected and -unaffected birth cohorts is reported by the study. Employing the same identification strategy with a different survey in a similar methodology as in the previous research, Spohr (2003) finds that the reform led to a significant increase in years of schooling and the probability of having at least 9 years of schooling. In turn, compulsory education is found to lead to significantly higher labor force participation as 2% and 5.2% and higher annual earnings as 5.8% and 16.7% for males and females, respectively.

Focusing on the effects of the same education reform on the education expansion and labor market outcomes from the perspective of gender disparities, Tsai et al. (2009) employs Taiwanese population censuses in a 2SLS regression and first-stage estimates conclude that although the 1968 reform resulted in respective 1.53 and 2.14

years increases in the educational attainment for males and females, the impact of increased education on the likelihood of employment of males and females is diverse. Accordingly, an additional year of education decreases the likelihood of employment of males by 2% whereas it increases the likelihood of employment of females by 4%. It is also found that increased years of education resulted in a shift in employment probability from the agriculture sector to the service, manufacturing, and commerce sectors for both males and females. Similar to previously reported increased level of schooling and moderate return on schooling as implied by the expansion of compulsory education in Taiwan, Zhang (2020) reports 0.17-0.32 years increase in overall educational attainment and 5.6% return on education as measured by the logarithm of wages.

A recent research by Korwatanasakul (2023) explores returns to schooling in Thailand using Regression Discontinuity on the 1978 compulsory schooling law which affected the birth cohort of 1968 and onwards. The first-stage regression results imply that the reform which extended obligatory years of schooling from 4 to 6 years, yielded about 4 years of additional schooling and the effect is statistically significant. Consistent with the large effects on years of schooling as estimated in the first stage, the IV estimates of returns to schooling are found approximately 8%, which is similar to those reported for Canada and the United Kingdom and returns are reported to be higher in urban areas, in the services than in the agricultural sector, and in the relatively underdeveloped northern and northeastern regions. In a cognate attempt, Fang et al. (2012) provide evidence related to China which increased compulsory education to 9 years in 1986. Hypothesizing that children less than 15 years old are the group affected by the law in a 2SLS regression, first-stage estimates suggest that the impact of Chinese compulsory schooling extension is statistically significant and positive such that compulsory schooling led to 0.79 years increase in total years of schooling attained. The second stage estimates imply that return on an additional year of schooling is found to be significant and equals to 20% which is stated to be higher than the returns found in previous studies conducted for other countries. Pursuing a parallel approach, Elsayed (2019) investigates the impact of primary compulsory schooling extension from 5 to 6 years starting from 2004-2005 school year on total years of schooling, post-primary attendance, and labor market outcomes of individuals born 1992 and onwards. It is reported that an extra year of primary education increases total years of schooling by between 0.63 and 0.76 years. Related to completing primary school and attending post-primary education outcomes, the reform is found to have positive yet insignificant effects on both. Finally, expanding primary education from 5 to 6 years appears to have substantial positive implications for employment status. According to the estimates, individuals influenced by the reform exhibit a higher likelihood of employment compared to those who are not influenced by the reform, with an estimated increase ranging from 2.3 to 3.1 percentage points. However, it is important to highlight that these effects do not achieve statistical significance. In a similar attempt to analyze the effect of compulsory schooling on educational attainment, Shidiqi and Choi (2023) provide evidence related to Indonesia which expanded compulsory schooling from 6 to 9 years in 1994. Similar to previous work, utilizing the discontinuity in educational attainments occurred between the birth cohorts before 1978 and onwards in an RDD analysis, obligatory schooling reform had a favorable impact on completed years of education by 1.79 years, the accomplishment of nine years of education by 19.3 percentage points, the enrollment in senior secondary education by 14.8 percentage points, the completion of a 12-year educational cycle by 11.1 percentage points, and no significant impact on the probability of university enrollment.

The preceding studies offer empirical insights regarding the impacts of compulsory schooling legislation. Research conducted across diverse countries suggests consistent effects on educational attainment, albeit demonstrating varying impacts on the returns associated with higher levels of schooling. The extensive body of empirical evidence concerning the impact of compulsory schooling laws prominently features significant findings from Türkiye, which extended mandatory education from 5 to 8 years in 1997 and further from 8 to 12 years in 2012. For example, Mocan (2014) examines the effects of the 1997 reform on middle school completion, wages, labor force participation, and investigates how these effects vary between genders and urban-rural location of residence. Adhering to a regression discontinuity analysis, those affected by the reform are identified based on birth year. Using two representative labor force surveys[23] conducted in 2011 and 2012, the first stage regression of a linear probability model suggests that the reform increased the probability of middle school graduation for males and females by 13.1 percentage

[23] This survey is Household Labor Force Survey conducted by TURKSTAT in Türkiye.

points and 17 percentage points, respectively. Additionally, the reform significantly increased the likelihood for urban males by 11.7 percentage points and for rural males by 17.0 percentage points to complete at least middle school. The impact was even greater for females living in urban areas, with the legislation resulting in a 17.8 percentage point increase compared to a 15.4 percentage point increase for those in rural areas. The second stage regression for the entire sample implies a return of approximately 10% for three more years of schooling, although no statistically significant return on the middle school diploma was found for males. However, the return on an extra three years of education for females is estimated at 43%, corresponding to approximately 14% return on an additional year of schooling. Based on the second stage results, the study finds no significant impact of increased schooling on either labor force participation or full-time work.

In their study, Kırdar et al. (2016) provide evidence related to the impact of the 1997 compulsory schooling reform specific to achieving equality in schooling outcomes across gender and urban-rural residence in Türkiye. Using another nationally representative survey[24] conducted in the years 2003 and 2008, and employing logistic regressions within a difference-in-differences framework, each grade completion status from 5th to 11th is examined by gender in urban and rural areas. According to the results of the analysis by gender in both urban and rural areas, there is a positive effect of the policy for both males and females in grades 6 to 8 and in grades 9 to 11. Furthermore, the results of the analysis of total years of educational attainment at age 15 and at age 17 by gender in both urban and rural areas reveal that total years of educational attainment at age 17 increases by about 1.3 years for rural males, by about 1.5 years for rural females, and by about 0.8 years for both urban males and urban females. The significant evidence related to the existence of spillover effects from the 1997 compulsory schooling reform in Dayıoğlu and Kırdar (2015) confirms previously reached conclusions that the reform led to an increased probability of high school and college completion from the regressions of the probability of completing high school, the probability of completing vocational school, or the probability of completing college (Mocan, 2014).

The conclusion that the return on increased education is significantly more pronounced for women in Türkiye due to compulsory schooling is further

[24] This survey is Turkish Demographic Health Survey conducted by Hacettepe University in Türkiye.

substantiated in the two regression discontinuity studies conducted by Aydemir and Kırdar (2017) and Torun (2018). These studies examine the same reform and utilize the same nationwide surveys as in Mocan (2014), spanning a longer time period such that the former one employs years between 2002-2013 and the period between 2004-2011 is employed by the latter. To estimate the causal link between schooling and wages both studies estimate 2SLS regression, and the first stage results of Aydemir and Kırdar (2017) demonstrate that the reform increased schooling by 0.59 years for males and 0.44 years for females. Similarly, Torun (2018) demonstrates that the 1997 reform is found to increase schooling: middle school degree attainment is raised by 17 percentage points for females and 11 percentage points for males. Furthermore, the high school completion rate is documented to increase by 3-4 percentage points whereas there is no significant impact reported in favor of completing beyond secondary education (Torun, 2018). These studies differ in their first-stage conclusion about the relative impact of the reform on genders. For example, while Aydemir and Kırdar (2017) reports a relatively larger effect of the reform on schooling of males than that on females, Torun (2018) documents the reverse. Nonetheless, this difference arises from the substantial increase in the employment probability of women with higher educational attainment, whereas no such difference is pronounced for men across different education groups (Dayıoğlu & Kırdar, 2009). Therefore, this disparity stems from the fact that the former study exclusively utilized a sample of wage-earning individuals. According to Aydemir and Kırdar (2017), the second stage estimate of returns to schooling is statistically insignificant for males whereas it is 3.8% for females. Likewise, the return on increased education due to compulsory schooling reform is approximately 9-10% for females while the effect is estimated at about 0-2% for males according to Torun (2018).

Akar (2021) investigates the impact of the 1997 reform on educational attainment, employment, and wages, with a focus on ethnic disparities between Kurds and Turks in Türkiye. Utilizing a novel dataset, the Konda Barometer, which details respondents' ethnic backgrounds from 2014 to 2017, within a regression discontinuity framework employing a linear probability model, the findings reveal that the compulsory schooling reform exacerbates the ethnic gap in educational outcomes between Kurdish and Turkish females at both compulsory and post-compulsory schooling levels. Specifically, the reform decreases the likelihood of completing at least 8 years of schooling by 12 percentage points. Additionally, the reform increases the rates of junior high school completion for both Kurdish and Turkish males, yet the ethnic gap persists between the two groups. The reform also generates spillover effects, enhancing the educational attainment of Turkish and Kurdish males beyond compulsory schooling levels. However, such effects are observed only for ethnic Turkish females, not for Kurdish females. In terms of employment outcomes, while the reform boosts labor force participation rates for both Kurdish and Turkish females, Kurdish females are less likely to be employed than their Turkish counterparts. Therefore, it is concluded that the ethnic disparities between the two groups persist. Similar conclusions are drawn for ethnic Turkish and Kurdish males as well. (Akar, 2021).

Studies by Erten and Keskin (2019) and Yıldız (2022) investigate the educational outcomes related to the last compulsory education reform enacted by the Turkish government in 2012. These studies utilize the discontinuity that occurred for individuals born from 1998 onwards to address recent changes in the educational attainment of Turkish youth. The study by Erten and Keskin (2019) examines the issue through the lens of childhood idleness, employing the same survey data as previous research (such as Mocan, 2014) and following a regression discontinuity framework. The effects of the 2012 reform on high school attendance, including vocational and academic high schools, are assessed for 15-18-year-olds. The results indicate a statistically significant RD estimate of a 3.2 percentage point treatment effect on overall high school attendance. Furthermore, the estimates show a significant increase of 4.4 percentage points in vocational high school attendance and an insignificant decrease of 1.9 percentage points in academic high school attendance. The study also reveals gender-specific effects: the reform led to increased vocational high school attendance for both females and males, including attendance at religious schools. Additionally, the reform had a positive impact on female distance high school attendance in its first year of implementation, although no significant effects were observed for male distance high school attendance or academic high school attendance overall.

In a recent examination of the link between compulsory schooling laws and school participation, Yıldız (2022) provides evidence regarding the 2012 education reform in Türkiye. This study leverages the discontinuity observed in birth cohorts from

1998 onwards, which were affected by the new policy, identifying these cohorts as the treatment group in a grade-by-grade analysis from 9th to 12th grade. The parametric and non-parametric estimates of the recent compulsory schooling extension are reported to be closely aligned, showing significant increases in the proportion of individuals completing at least grades 9 and 10 by 5 percentage points and 3.7 percentage points, respectively. The impact diminishes beyond grade 10 according to parametric results, while non-parametric results indicate significant increases in the completion rates of grades 9, 10, 11, and 12 by 4.48, 3.33, 4.28, and 8.29 percentage points, respectively.

The research literature extensively examines the effectiveness of compulsory schooling laws in enhancing educational attainment and the extent to which this effectiveness translates into increased returns on education, drawing upon abundant empirical evidence from both developed and developing countries. Türkiye, which implemented two compulsory schooling laws—extending schooling from 5 to 8 years in 1997 and from 8 to 12 years in 2012—serves as a notable case study for investigating educational and economic outcomes, given its sizable youth population. A review of the research conducted in Türkiye reveals that considerable attention has been devoted to the 1997 reform, reflecting the passage of time and the increased availability of relevant data. Although a few studies have investigated the intended effects of the 2012 reform, such as high school attendance and graduation, the potential spillover effects of the reform on educational levels beyond its intended scope, such as university graduation and labor market outcomes, have yet to be thoroughly examined. Consequently, in line with previous scholarship, this thesis endeavors to address this gap in the literature by investigating these outcomes, leveraging the discontinuity arising from exposure to the reform across different birth cohorts.

4.3. Overview of Turkish Compulsory Schooling Legislation

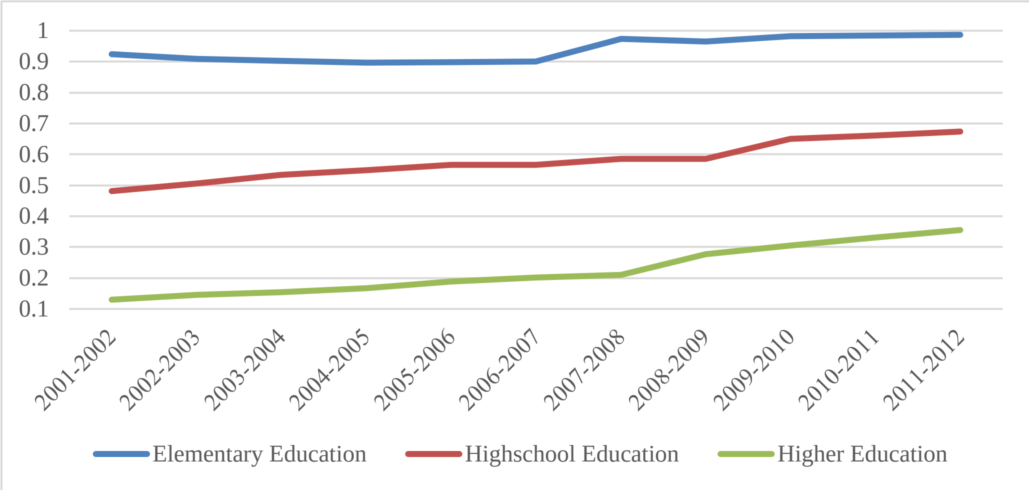
Since the establishment of the Turkish Republic in 1923, the compulsory education system initially has comprised only five years of primary schooling. The Basic Education Law (No. 4306), introduced in 1997, marked a significant reform by extending compulsory education from 5 years to 8 years, encompassing both primary and middle school education. Prior to this reform, the net enrolment rate at the primary school level was 89.4%, while the enrolment at the secondary school level was 52.8%[25]. Four years after the enactment of the law, coupled with the construction of new classrooms, hiring of additional teachers, and a campaign to promote middle school education, the net enrollment rate at the compulsory schooling stage increased to 95.3% (Aydemir & Kırdar, 2017).

Prior to 2012, basic education in Türkiye adhered to an uninterrupted eight-year model. However, a significant structural revision took place in 2012 (Law No.6287), resulting in a segmented format comprising four years of primary school followed by four years of middle school further followed by four years of high school education. Additionally, the commencement of the 2012-2013 academic year marked the transition of high school education from non-compulsory to compulsory status. The 2012 educational reform resulted in an expansion of the mandatory schooling duration from 8 to 12 years, often commonly referred to as the “4+4+4” schooling system.

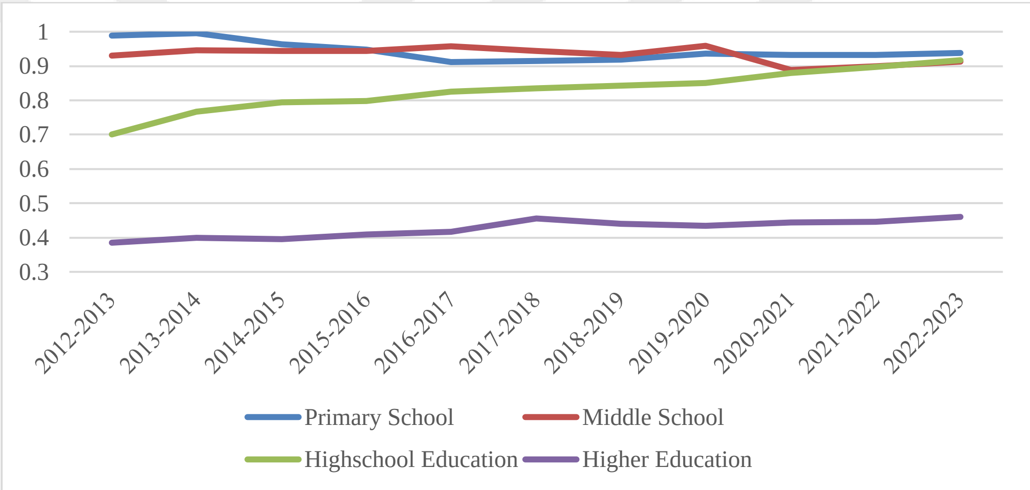
According to Figure 4.1, which depicts enrollment rates by educational year and level before and after the 2012 reform, it is observed that net enrollment in high schools has steadily increased following the implementation of the reform in Türkiye, while net enrollment in higher education has remained relatively stable at around 45%. However, notable decreases in net enrollment rates, especially during the 2020-2021 and 2021-2022 academic years for middle school, and the 2016-2017, 2017-2018, and 2018-2019 academic years for primary school, are observed when compared to the period of eight years of compulsory education under the elementary school system. The rate of net enrollment in high school has shown a persistent increase both before and after the implementation of the 2012 reform, suggesting that the compulsory schooling expansions of 1997 and 2012 have been effective in encouraging students to pursue higher educational attainment. The most significant increase in the net enrollment rate is observed in higher education during the 2007-2008 and 2012-2013 academic years.

[25] According to MoNE (Ministry of National Education) Educational Statistics.

Figure 4.1. Net Enrollment Rates by Year and Level of Education[26]



(a)



(b)

Note: Panel (a) belongs to the period before 2012 Reform and Panel (b) belongs to period after the reform.

Table 4.1 tracks the record of compulsory schooling legislation and its scope in Türkiye. As observed in the table, there are two major educational reforms: the 1997 reform and the 2012 reform. In addition to these, a minor reform in 2005 extended the duration of high school from 3 to 4 years, without altering the scope of compulsory schooling. It can also be deduced from the table that, unlike previous reforms and implementations, the 2012 reform permitted high school education to be conducted not only in face-to-face settings but also remotely, should students opt for such an arrangement.

[26] According to MoNE Education Statistics.

Table 4.1. Evolution of Compulsory Schooling in Türkiye

Before 1997	1997-2005	2005-2011	2012-Onwards
Primary School 5years Compulsory **Middle School** 3years Non-compulsory	**Elementary School** 5 years Primary School 3 years Middle School Compulsory	**Elementary School** 5yearsPrimary School 3 years Middle School Compulsory	**Primary School** 4years Compulsory **Middle School** 4years Compulsory
High school 3years Non-compulsory Face-to-face	**High school** 3years Non-compulsory Face-to-face	**High school** 4years Non-compulsory Face-to-face	**High school** 4years compulsory Face-to-face or Remote

4.4. Data & Methodology

4.4.1. Data & Identification Method

The dataset employed in the present study comprises the HLFS[27], which is administered by TURKSTAT. HLFS is annually conducted since 2006 in Türkiye in order to gather information related to demographics, educational attainment, economic situation, employment, income and health status of all members of the households that live within the borders of the country. Specifically, the data related to the last completed schooling/education level, current enrollment status in addition to several demographic characteristics of age group, completed age, gender, size of the household, income, number of hours worked, residence of region are provided in the survey. HLFS is deemed useful for this study as its objective is to examine the impact of the most recent compulsory schooling legislation change on final educational attainment, employment status and earnings of individuals living in Türkiye.

In April 2012, the Turkish parliament enacted a legislation to extend compulsory schooling from 8 to 12 years. The policy was first implemented in 2012-2013 school

[27] HLFS is an abbreviation of Household Labor Force Survey conducted by Turkish Statistical Institute TURKSTAT.

year. This means that 8th graders (and those who are at lower grades) in the 2011-12 school year were required to complete 12 years of schooling, while those who had already completed 8th grade could drop out. Due to the alignment of school starting age with the calendar year and assuming that individuals start primary school at age of 6 together with the fact that the total duration in primary and middle schools equals to 8 years, individuals born after January 1998 were more likely to be 8th graders in the 2011-2012 school year, making them subject to the new compulsory schooling requirement. Consequently, individuals born before January 1998 were allowed to drop out after 8 years of education, whereas those born after January 1998 were mandated to complete 12 years of schooling.

The discontinuity in the analysis, which takes place between 1997 and 1998 birth-cohorts, is fuzzy due to two reasons: First, since not all children start school at age 6, some children in the 1997 birth-cohort in particular those who were born on months of September, October, November and December had an option to start school one year later due to the fact that Turkish law[28] enables those who were born in the last four months of the year can postpone starting primary school by a year. This leads to the situation that those children may have started primary school with 1998-borns meaning that they started school late and was affected by the new policy (although they shouldn't be because they were born before 1998). In summary; while the survey provides information on both the year and month of birth, the inability to track each individual's school starting age undermines the capacity to precisely identify treatment allocation based solely on the discontinuity in birth year or month. Second, individuals may have committed grade repetition. Unfortunately, neither HLFS nor other nationally representative surveys provide information related to respondents' grade repetition status in the past. As a consequence, there exists a scenario where individuals who should belong to the treatment group are categorized into the control group. Thus, one ends up with two alternative solutions: First, sharp RDD can be employed on a sample which excludes birth cohorts of 1997 and 1998, since somebody who was born in 1996 and before, or was born in 1999 and onwards is expected to be definitely exposed to the new policy. Or, alternatively, one can

[28] According to the *Letter of Preschool Enrollment* of *MoNE Preschool and Elementary School Institutions Regulation* in Türkiye, the school starting age is not determined by a student's age in September; rather, students who reach 69 months of age by the end of September are eligible to start school in September. This implies that children who were born in September, October, November, or December are afforded the opportunity to start school a year later than their counterparts.

accept that sharp RDD design isn't feasible in this situation leading us to employ fuzzy RDD[29].

Table 4.2 briefly presents the number of observations in two categories of birth year variable for each category of high school graduation status variable (HGR). For instance, there are 10796 observations who are not high school graduates among those who were born after 1998 in sample A. Similarly, there are 3658 observations who are high school graduates and were born after 1998. Other rows can be interpreted in the same way as described. One can deduct from this table and given the fact that the 2012 reform compelled students complete high school education and those who were born in 1998 and onwards are affected by it, the probability of individuals who are expected to complete high school as mandated by law (as indicated by a birth year after 1998 in the running variable) but did not, is 0.44, not 0. As a consequence, there exist individuals who are in the control group although they shouldn't be. The same situation is also evident in Sample B: the probability that who are supposed to complete high school as the law induced yet didn't, is equal to 0.592 not 0.

Table 4.2. The Number of Observations for High school Graduation Status and Running Variable

HGR	Running Variable	Number of Observations	Probability
Sample A			
0	Birth Year ≥ 1998	10388	0.44
0	Birth Year < 1998	13455	0.56
1	Birth Year ≥ 1998	3658	0.2
1	Birth Year < 1998	14973	0.8
Sample B			
0	Birth Year ≥ 1998	74612	0.592
0	Birth Year < 1998	51413	0.408
1	Birth Year ≥ 1998	34000	0.342
1	Birth Year < 1998	65368	0.658

Note: High school graduation status (HGR) is a binary variable which takes value of 0 if an individual has an education below high school degree, and it takes value of 1 if an individual has at least high school diploma. The table depicts the values of HGR against being exposed to the compulsory schooling law, i.e., being born in 1998 and onwards, along with the corresponding probabilities of occurrence for each case.

[29] Both of the methods are employed in previous studies. For example: Mocan (2014), Aydemir and Kırdar (2017) among others, are advocates of the fuzzy RDD whereas Elsayed (2017), Yıldız (2022) among others, followed the sharp RDD.

Before 2012 reform in Türkiye, the education system consisted of compulsory 8 years of education which included 5 years of primary schooling followed by 3 years of middle schooling. In 2012, the government expanded compulsory schooling from 8 to 12 years, by doing so high school education is contained within the new compulsory schooling legislation. This policy was nationally implemented and highly linked to the contemporaneous political events. Given that the 2012 reform intended to cover high school education period and our objective is to assess its effectiveness in both intended and spillover periods of education (i.e. high school attainment and university degree attainment) as well as in employment status and wages; those who are at ages between 17 and 30 at the time of survey constitute our primary sample akin to the sampling procedure which is followed in previous researches[30]. The minimum age is restricted to 17 because an individual can graduate from high school at the age of 17 at the earliest in Türkiye, and age of 30 is convenient to analyze labor market outcomes as individuals have progressed through university education, find a job and gain job experience over time. Moreover; 2013-2022 waves of HLFS will be pooled in the present study, as the year 2013 corresponds to the commence of the 2012 reform and 2022 is the latest available survey.

Table 4.3 summarizes the birth year of 17-30 year old individuals by age and survey year. The birth years starting from 1998 and onwards are shaded grey and represent treatment group, and the birth years in white cells represent the control group of the study. The birth years in bold which correspond to those born in and before 1986 are excluded from the study (as those were subject to 5 years of compulsory schooling) in order to sterilize the effect of 2012 legislation which increased compulsory schooling to 12 years from the effect of 1997 legislation which increased compulsory schooling to 8 years. Therefore, we will be investigating the effect of compulsory schooling expansion from 8 to 12 years exactly.

[30] For example: Aydemir and Kırdar (2017), Torun (2018), Mocan (2014) and Yıldız (2022).

Table 4.3. Birth Year By Age and Survey Year

Age	Survey Year									
	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
17	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
18	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
19	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
20	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
21	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001
22	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
23	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
24	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998
25	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997
26	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
27	**1986**	1987	1988	1989	1990	1991	1992	1993	1994	1995
28	**1985**	**1986**	1987	1988	1989	1990	1991	1992	1993	1994
29	**1984**	**1985**	**1986**	1987	1988	1989	1990	1991	1992	1993
30	**1983**	**1984**	**1985**	**1986**	1987	1988	1989	1990	1991	1992

Note: Treatment Group is shaded grey, whereas control group is shaded white[31]. Birth years in bold are those who were subject to 5 years of compulsory schooling before 1997 reform.

Table 4.4 presents ages of individuals considered in the study based on their assignment status to treatment and control groups corresponding to each year of the survey. It is mainly observed from the table that treatment and control groups do not overlap in their coverage of ages.

[31] Compulsory schooling has been extended from 8 to 12 years in 2012 in Türkiye starting from the 2012-2013 school year. As a result, students in 8th grade or lower in the 2011-2012 school year had to complete 12 years of schooling, while those who had already finished 8th grade could drop out. Given that school starting age is 6, students born after January 1998 were affected by this new requirement and had to finish all 12 years (treatment group), whereas those born before January 1998 could leave after 8 years (control group). We also exclude those who were affected by 1997 compulsory schooling law which extended compulsory schooling from 5 to 8 years from control group in order to measure the effect of rising compulsory schooling from 8 to 12 years. Therefore those who were subject to 5 years of compulsory schooling are excluded from the control group.

Table 4.4. Ages by Sample and Survey Year

	Survey Year									
	2013	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
Whole Sample	17-26	17-27	17-28	17-29	17-30	17-30	17-30	17-30	17-30	17-30
Treated Group	DNE	DNE	17	17&18	17-19	17-20	17-21	17-22	17-23	17-24
Control Group	17-26	17-27	18-28	19-29	20-30	21-30	22-30	23-30	24-30	25-30

Note: DNE stands for Does Not Exist.

The identification of individuals subject to the educational reform relies on both their school starting age and year of birth. Consequently, exposure to the compulsory schooling reform is quantified by generating a binary variable, CSL, which is equal to 1 for individuals born after 1998 and 0 otherwise.

HLFS categorizes educational attainment of respondents in terms of highest level successfully completed as no schooling, primary school, secondary and vocational secondary school, elementary school, high school, vocational and technical (VAT, thereafter) high school, 2 or 3 year higher education, 4 year- university education, 5 or 6 year-university education, master degree and doctorate degree. In the present analysis, intended as well as spillover effect of the legislation will be examined by generating number of years of schooling variable.

In addition to reform's effect on educational attainment, we aim to explore the influence of 2012 reform on early labor market outcomes. Based on HLFS, it is possible to determine a respondent's current employment status at the time of survey, enabling us to construct a dummy variable, which is EMP and it takes a value of 1 if the respondent is employed, and it takes 0 otherwise. HLFS also includes the information on income earned last month which can be considered as a reasonable proxy for monthly earnings. In addition, HLFS contains individual data on total number of hours worked in a week. Using this information together with monthly income, and given that a month consists of 4.3 weeks; hourly wage is calculated as:

$$Hourly\ Wage = \frac{Monthly\ Income}{Weekly\ Working\ Hours \times 4.3} \tag{4.1}$$

where dividing the monthly income by 4.3 yields the weekly income, and further dividing the weekly income by the number of weekly working hours gives income per hour i.e. hourly wage.

4.4.2. Empirical Methodology

The regression discontinuity design (RDD) is one of the most widely used quasi-experimental methods to assess the impact of an intervention. In this context, treatment effect is estimated when the status of receiving treatment is determined by a running variable (forcing variable, assignment variable) and a pre-determined cutoff value (threshold) of the running variable. As the empirical analysis in this thesis focuses on evaluating the effects of the 2012 compulsory schooling reform on educational and labor market outcomes such as individuals' high school and university graduations, employment status and earnings; the RDD methodology is utilized.

RDD is categorized into sharp RDD and fuzzy RDD based on the likelihood that individuals on either side of the threshold of the assignment variable receive the treatment intervention. On the one hand, sharp RDD denotes a scenario where the assignment variable definitively determines treatment, meaning all individuals on one side of the assignment variable receive treatment while those on the other side do not. Fuzzy RDD on the other hand, pertains to a scenario in which the assignment variable probabilistically determines whether an individual receives the treatment intervention. The estimation procedure of treatment effect differs between sharp RDD and fuzzy RDD. In sharp RDD, treatment effect can be estimated by comparing the two groups on both sides of the threshold, whereas in fuzzy RDD the treatment effect can be estimated through two-stage least squares (2SLS, thereafter) regression.

In the current research, birth year of individuals is the assignment variable, and it is reasonable to assume that birth year affects earnings or employment only through the assignment mechanism. Moreover, the birth year of an individual is not expected to be related to ability, parental choice or other unobserved confounding effects that might influence the labor market prospects. Furthermore, the birth year of an individual is not expected to be intentionally manipulated to derive future expected benefits. To summarize, being obliged to have more schooling as a result of compulsory schooling policy expansion in 2012 is a valid instrument for endogenous variable schooling.

In order to assess the effect of 2012 reform on outcome variables that are briefly outlined above, the following 2SLS regressions will be estimated. The first stage equation is as follows:

$$Schooling_i = \alpha_0 + \alpha_1 CSL_i + \alpha_2 g(Birth\,Year_i - 1998) + X'\theta + u_i \qquad \textbf{(4.2)}$$

$$CSL_i = \begin{Bmatrix} 1,\ if\ Birth\,Year_i \geq 1998 \\ 0,\ if\ Birth\,Year_i\ < 1998 \end{Bmatrix}$$

The second stage equation is as follows:

$$Outcome_i = \beta_0 + \gamma \widehat{Schooling_i} + \beta_1 g(Birth\,Year_i - 1998) + X'\Psi + v_i \qquad \textbf{(4.3)}$$

where the descriptions of variables are as:

- In equation (4.2), $Schooling$ denotes being completed at least high school (HGR) and being completed at least university (UGR). Both HGR and UGR are binary and take value of 1 if the respondent is at least high school graduate (and at least university graduate for UGR) and 0 otherwise,
- CSL is a dummy variable which takes value of 1 if the subject is exposed to the new policy and 0 otherwise,
- $Birth\,Year$ is the running variable denoting the birth year of each subject, and following the prior studies, we employ polynomial terms of centered birth year. The centered birth year[32] is calculated as the birth year of the respondent minus 1998 cutoff. Therefore $g(.)$ is a function of the birth year, specified by polynomial terms of the first, second, third, and fourth degrees.
- X includes age of each subject at the time of the survey (as a proxy for working experience), survey year (as a proxy for time specific characteristics such as economic conditions) and residence of living region at the NUTS-1 level.
- In equation (4.3), the outcome variables are logarithm of earning in the previous month ($log\,EARN$), logarithm of hourly earnings ($\log HOURLY\ WAGE$), employment status (EMP) and labor force participation (LF) that will be separately estimated. Employment status and

[32] Centered birth year can be positive or negative depending on the birth year of the subject.

labor force participation status variables are binary, taking value of 1 if the respondent is employed (or in the labor force) and 0 otherwise,

- $\widehat{Schooling}$ in equation (4.3) denotes estimated values / probabilities from equation (4.2). The remaining right-hand side variables are the same as in the first stage equation. All the equations are separately estimated for female and male samples.

The instrumental variable (IV) approach enables us to discern the causal impact of education on wages by leveraging exogenous variation in educational attainment levels. Specifically, the IV model estimates the local average treatment effect (LATE, thereafter) for individuals who comply with the treatment due to exposure to compulsory schooling reforms but would not receive the treatment otherwise. Although this subset of compliers may not represent the entire population, Oreopoulos (2006b) suggests that an increase in the proportion of the population exposed to policy changes causes LATE estimates to converge towards the average treatment effect (ATE, thereafter). Given that the Turkish compulsory schooling reform which is applied nationwide and affected a substantial portion of the population across various birth cohorts, the estimated LATE converges towards ATE (Aydemir & Kırdar, 2017).

4.4.3. Descriptive Statistics

HLFS collects information about various characteristics of its respondents such as gender, age, birth year, region of residence, last completed education level, birth place, income earned last month, employment status etc. To investigate four primary labor market indicators, namely monthly income, hourly wage, employment status and labor force participation status, two distinct samples, denoted as Sample A and Sample B, are formed from pooled HLFS data spanning the years 2013 to 2022. This is necessitated by the fact that when considering income earned in the previous month, the sole outcome for employment status becomes being employed, thereby resulting in the exclusion of cases pertaining to unemployment and being out of the labor force. Consequently, Sample A will be employed in income regressions whereas Sample B will be employed in employment regressions[33].

We have opted to exclude college graduates[34] from our primary sample employed in estimations with schooling variables of high school attainment status and number of years of schooling for several reasons. Firstly, our sampling framework encompasses all individuals aged 17 and 30, thus naturally skewing towards a younger demographic where college attainment is less prevalent. Secondly, owing to the recent implementation of the policy under consideration, the demographic profile of treated individuals tends to exhibit a lower average age compared to their non-treated counterparts within our sample. These factors collectively contribute to a higher proportion of college graduates among the non-treated cohort relative to the treated cohort. The omission of observations with college degrees yields a sample wherein the treated and control cohorts exhibit greater similarity in terms of their educational attainment. Following the exclusion of missing data, adjusting nominal income with consumer price index (CPI[35], where 2013 = 100), omitting the upper and lower 1 % of the observations in the income distribution to exclude outliers, the final sample sizes are 42,474 for Sample A and 225,393 for Sample B, encompassing individuals aged 17 to 30 years.

Table 4.5 documents the total number of observations and corresponding percentages of variables that we considered for Sample A in this study. Male and female respondents make up about 68% and 32% of the sample, respectively and most of them live in TR1 (i.e. Istanbul) region followed by TR5 (i.e. West Anatolia), TR3 (i.e. Aegean region), TR6 (i.e. Mediterranean region), and TR4 (i.e. East Marmara) regions. Schooling attainment variables are constructed out of the question of last attained educational level which is presented in eight categories in the survey. Based on this question, a binary variable denoting at least high school graduate (HGR), a binary variable denoting at least university graduate (UGR) and the number of years of schooling in education (SCH) are constructed. Approximately 44% of Sample A

[33] The main difference between Sample A and Sample B relies in that the former one consists of employed individuals, only. Sample B, on the other hand includes those who are unemployed and out of labor force as well.

[34] In the estimations with schooling variables proxied by university degree attainment status, we didn't commit such an exclusion in order to avoid artificial introduction of university graduation after the cutoff of 1998 in birth year.

[35] CPI values are driven from World Bank, World Development Indicators.

graduated high school while 56% of the sample has attained schooling level lower than high school. In terms of university degree attainment, most of the respondents in Sample A has lower than university degree, only about 2.3 % of the respondents had at least university degree[36]. The status of being exposed to 2012 reform is constructed based on birth year question of the survey and it is a binary variable denoted by CSL taking value of 1 if the respondent was born in 1998, onwards and 0 if the respondent was born before 1998. Whereas 43% of the respondents are exposed to the 2012 reform (treatment group), 57% of the respondents are not (control group). Finally, most of the respondents were born in Türkiye corresponding to 99.4% of the sample.

Table 4.5. Number of Observations and Percentages of Variables for Sample A

Variable Name & Description	Number of Observations	Percentage
Gender		
Male (1)	28854	67.9
Female (2)	13620	32.1
NUTS-1		
TR1	6642	15.6
TR2	2379	5.6
TR3	4629	10.9
TR4	4500	10.6
TR5	5825	13.7
TR6	4544	10.7
TR7	2545	5.9
TR8	3003	7.1
TR9	1096	2.6
TRA	1941	4.6
TRB	2372	5.6
TRC	2998	7.1
HGR		
At Least High school Attainment (1)	18629	43.9
Less than High school Attainment (0)	23845	56.1
UGR		
At Least University Attainment (1)	993	2.3
Less than University Attainment (0)	41481	97.7

[36] This is due to previously explained exclusion of college graduates from control group. Before the exclusion, about 27% of the respondents had at least university degree in the whole sample.

Table 4.5.contiued

Variable Name & Description	Number of Observations	Percentage
CSL		
Exposed to 2012 Reform (1)	18303	43.1
Not Exposed to 2012 Reform (0)	24171	56.9
BIRTH PLACE		
Türkiye (1)	42201	99.4
Abroad (2)	273	0.6
Sample A	**42474**	**100**

Table 4.6 documents the total number of observations and corresponding percentages of variables that we considered for Sample B in this study. Male and female respondents make up about 53% and 47% of the sample, respectively and the sample is more balanced in terms of gender than Sample A. Most of the respondents in Sample B live in TR5 (i.e. West Anatolia) region followed by TR6 (i.e. Mediterranean region), TR1 (i.e. Istanbul), TR3 (i.e. Aegean region), and TRC (i.e. Southeast Anatolia) regions. Similar to the previously followed procedure, schooling attainment variables are constructed out of the question of last attained educational level. Approximately 44% of Sample A graduated high school while 56% of the sample has attained schooling level lower than high school. University degree attainment in Sample B is much rarer than Sample A such that about 98.7 % of respondents has lower than university degree. Exposition to 2012 reform is denoted by CSL variable as previously explained and about 59% of the respondents are exposed to the reform (treatment group) while about 41% of them aren't (control group). 28.5% of the respondents in Sample B are employed and 35.2% of them are in the labor force. Finally, most of the respondents were born in Türkiye corresponding to 98.7% of the sample.

Table 4.6. Number of Observations and Percentages of Variables for Sample B

Variable Name & Description	Number of Observations	Percentage
Gender		
Male (1)	120209	53.3
Female (2)	105184	46.7
NUTS-1		
TR1	24612	10.9
TR2	10895	4.8
TR3	23173	10.3

Table 4.6.continued

Variable Name & Description	Number of Observations	Percentage
TR4	18687	8.3
TR5	27547	12.2
TR6	24812	11
TR7	15554	6.9
TR8	16834	7.5
TR9	8949	4
TRA	15419	6.8
TRB	17314	7.7
TRC	21597	9.6
HGR		
At Least High school Attainment (1)	99368	44.1
Less than High school Attainment (0)	126025	55.9
UGR		
At Least University Attainment (1)	2889	1.3
Less than University Attainment (0)	222504	98.7
CSL		
Exposed to 2012 Reform (1)	132808	58.9
Not Exposed to 2012 Reform (0)	92585	41.1
BIRTH PLACE		
Türkiye (1)	222430	98.7
Abroad (2)	2963	1.3
EMP		
Employed (1)	64298	28.5
Unemployed (0)	161095	71.5
LFP		
In the labor force (1)	79243	35.2
Out of labor force (0)	146150	64.8
Sample B	**225393**	**100**

Table 4.7 presents summary statistics of logarithm of income earned last month, the logarithm of hourly wage, consumer price index, age at the time of survey, birth year of the respondent and centered birth year which is calculated as birth year minus 1998 cutoff and the number of years of schooling in education. On average,

logarithm of income earned last month is equal to 6.656 with a standard deviation of 0.65. The minimum value of this variable is equal to 4.777 due to an adjustment made to income earned last month, where the observations between the 1st and 99th percentiles are kept. The average of logarithm of hourly wage is equal to 1.46 with a standard deviation of 0.51. The minimum and maximum values of this variable are equal to 0.15 and 2.97, respectively. The mean ages of respondents at the time of HLFS conducted are equal to 21.6 years and 19.9 years for Sample A and Sample B, respectively. The variation in age variable appears to be slightly more in Sample A than Sample B. Since the lower and upper boundaries of both samples were set at ages 17 and 30, respectively, the minimum and maximum age values are equal to 17 and 30. This leads to minimum and maximum year of birth being equal to 1987 and 2005, respectively. The mean birth year in Sample A is calculated as 1996 and it is 1998 for Sample B. By definition the centered birth year variable is calculated as year of birth minus 1998 cutoff for both samples and on average, respondents were born before the cutoff of 1998. Consistent with the pre-set upper and lower bounds in age and birth year variables, the upper bound of centered birth year is equal to 7 and the lower bound of centered birth year is equal to 11. Additionally, the number of years of schooling for each respondent is deduced based on the information in last education level completed together with year of birth. However, the value for this variable is bounded by 18 years because HLFS combines the schooling status of a university degree and above as "university degree and more" for all years up to 2020. On average, the number of years of schooling that respondents in both samples attained is something between 12 years with a standard deviation of 1.97 and 1.84 for samples A and B, respectively.

Table 4.7. Summary Statistics of Variables for Sample A and Sample B

Variable Name	Description	Mean	Standard Deviation	Min	Max	Median
log(Income)	Logarithm of income earned last month	6.656	0.65	4.777	8.246	6.887
log(Hourly wage)	Monthly income / (Weekly working hours× 4.3)	1.46	0.51	0.15	2.97	1.52

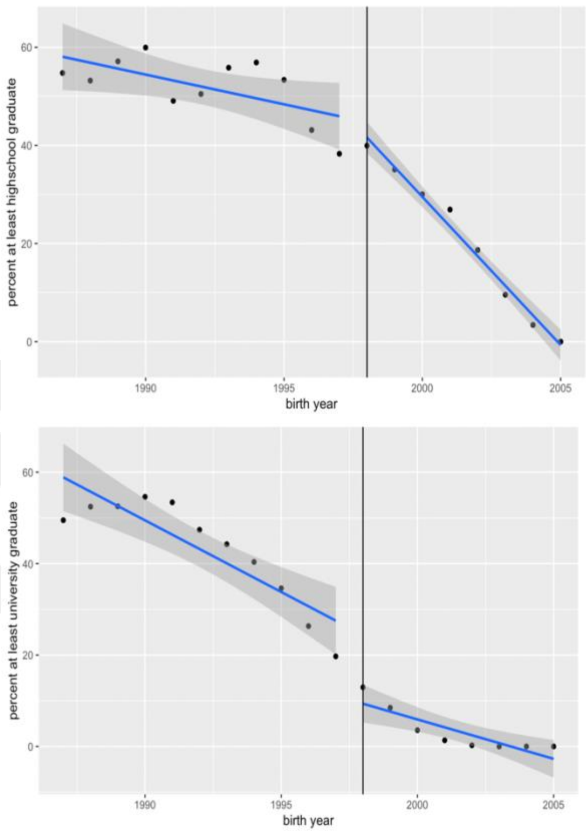
Table 4.7.continued

Variable Name	Description	Mean	Standard Deviation	Min	Max	Median
CPI	Consumer Price Index (2013=Base)	195.4	97.4	100	435.2	163.3
Age (Sample A)	Age at the time of survey	21.6	3.65	17	30	21
Age (Sample B)	Age at the time of survey	19.9	3.12	17	30	19
Birth Year (Sample A)	Year of birth	1996	4.28	1987	2005	1997
Birth Year (Sample B)	Year of birth	1998	3.93	1987	2005	1998
Birth Year Centered (Sample A)	Year of birth - 1998	-1.6	4.28	-11	7	-1
Birth Year Centered (Sample B)	Year of birth - 1998	0.0651	3.93	-11	7	0
Years of Schooling (Sample A)	Number of years in education	12.29	1.97	1	18	12
Years of Schooling (Sample B)	Number of years in education	12.42	1.84	1	18	12

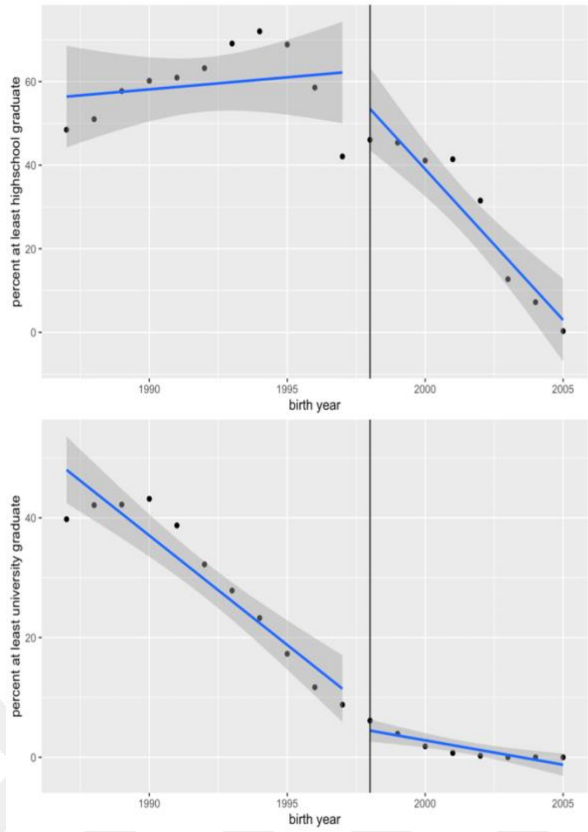
4.4.4. Trends in the Outcome Variables

In order to check whether there is a discontinuous change in the outcome variables at cut-off of the running variable, the percentage of individuals who completed at least high school and at least university against birth year is plotted in Figure 4.2. Panel (a) belongs to Sample A and panel (b) belongs to Sample B. The black vertical line in each of these plots passes through 1998 cut-off. Therefore; while the left-hand-side of the line pertains to those who are not affected by 2012 reform, the right-hand-side of the line belongs to those who are affected by the reform. A visual inspection of all graphs in Figure 4.2 reveals a prominent downward jump at the cutoff as well as a change in slope in percentage of high school and university completion for Sample A. For Sample B, there is a upward jump in percentage of high school completion which can be attributed to existence of the reform while for university completion there is a downward jump at the cutoff. For both samples except that high school completion in Sample B, the percentage of high school completion as well as university completion are higher for older individuals as implied by the decreasing trend.

Figure 4.2. Fraction of Individuals Attained at least Selected Education Level



(a)

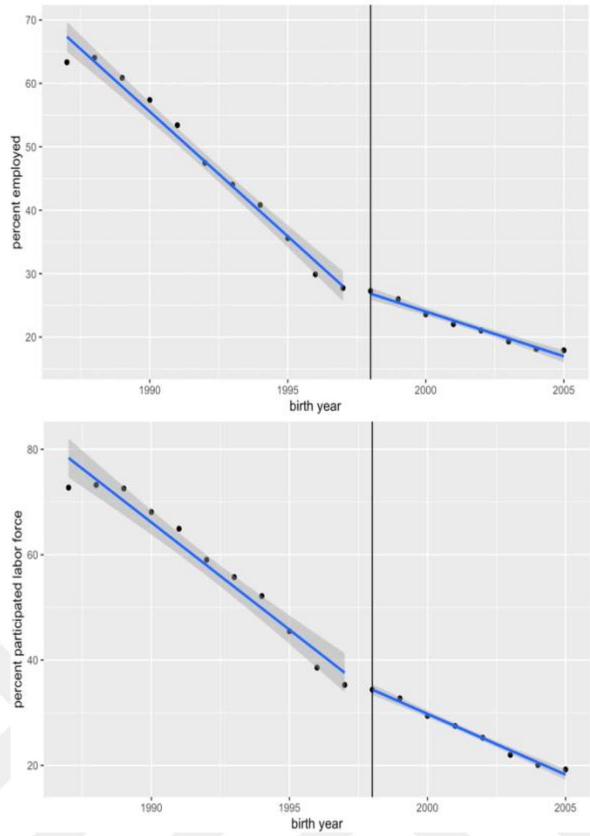


(b)

Note: Black vertical line passes through 1998 cut-off. First-order linear polynomials are fit to the left and right of the cut-off with 95% confidence interval.

Figure 4.3 replicates the same procedure as in Figure 4.2 and checks whether there is a discontinuous change in the outcome variables of employment and labor force participation status at 1998 cut-off in Sample B. Upon visual inspection of these graphs, although there is no apparent discontinuity like the previous jumps at the cutoff value, a change in slope is observed in these graphs as well. In addition, both employment and labor force participation percentages exhibit downward trend over the birth cohorts studied.

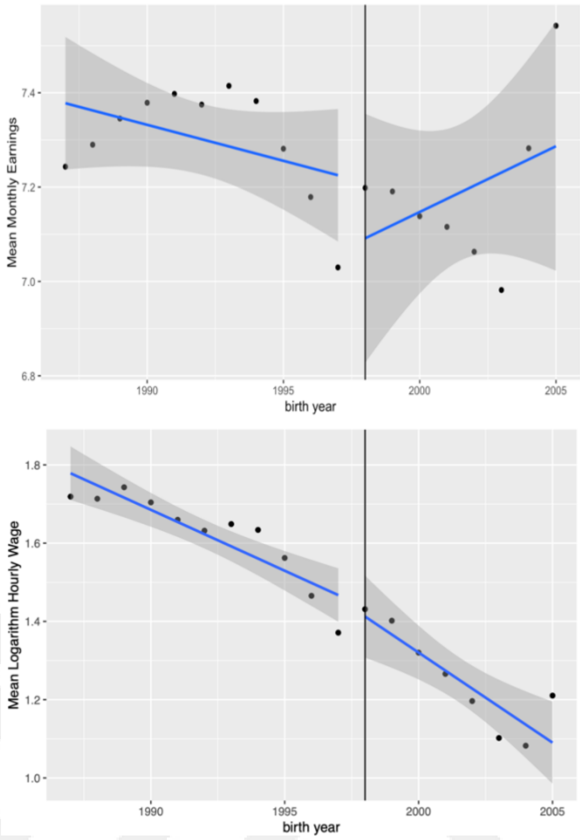
Figure 4.3. Fraction of Individuals Employed and in the Labor Force



Note: Black vertical line passes through 1998 cut-off. First-order linear polynomials are fit to the left and right of the cut-off with 95% confidence interval.

Figure 4.4 provides mean logarithm of income by year of birth for treatment and control groups in sample A. Each point in the graph refers to average of logarithm of income and average of logarithm of hourly wage for each birth cohort. As shown in this figure, there is an immediate jump in both monthly income and hourly wage outcomes at the cutoff value i.e. after the policy implementation. Furthermore, the slopes of the linear polynomials fitted to the left and right of the 1998 cutoff differ apparently, with the slope of the fit becoming steeper after the policy change.

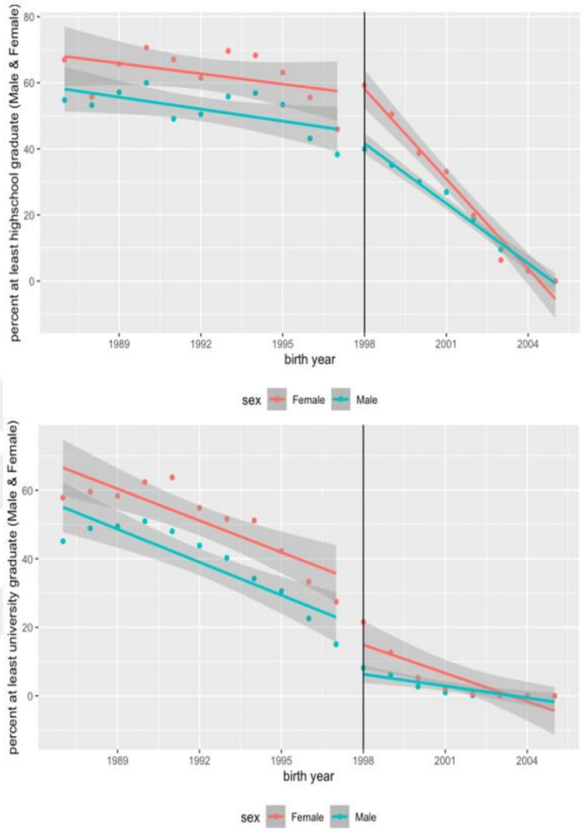
Figure 4.4. Mean Logarithm Income and Mean Logarithm Hourly Wage by Birth Year



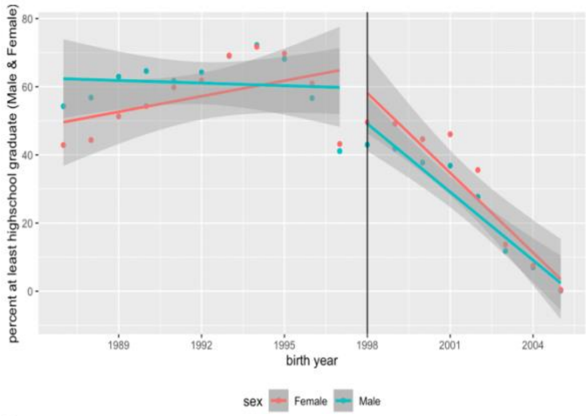
Note: Black vertical line passes through 1998 cut-off. First-order linear polynomials are fit to the left and right of the cut-off with 95% confidence interval.

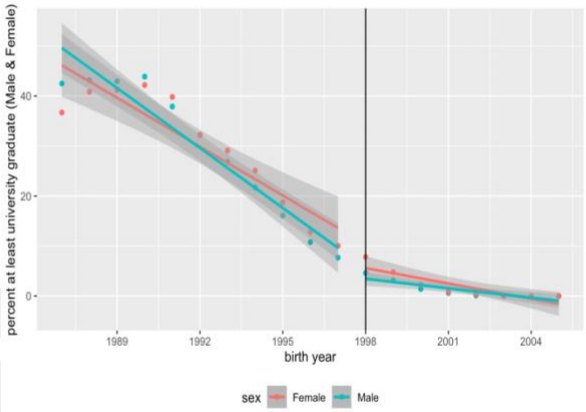
When we separately examine the female and male samples, the impact of the 2012 reform on the specified outcome variables becomes more pronounced. Figures 4.5, 4.6 and 4.7 show time trends in the same outcome variables for female and male samples before and after the reform. It can be observed from Figure 4.5 that the fraction of individuals who are at least high school graduates has decreased over birth cohorts. Besides, an upward jump in the proportion of at least high school graduates at the cutoff is observable in both samples. Conversely, a downward jump in the proportion of those who are at least university graduates is observed at the cutoff for both samples. Moreover, female birth cohorts are more tend to graduate high school than male cohorts however this seems to be reversed after 2004 birth cohort. Related to gender gap in university graduation, the same conclusions drawn for high school graduation are also valid together with that fraction of females and males who are at least university graduates are substantially lower than the fraction of females and males who are at least high school graduates. Finally, while the high school graduation percentage of Sample B; which includes employed as well as unemployed and out of labor force individuals; is quite close to that of Sample A; which consists of employed individuals only; the university graduation percentage in Sample B is substantially lower compared to that of Sample A.

Figure 4.5. Fraction of Individuals Attained at least Selected Education Level by Gender



(a)



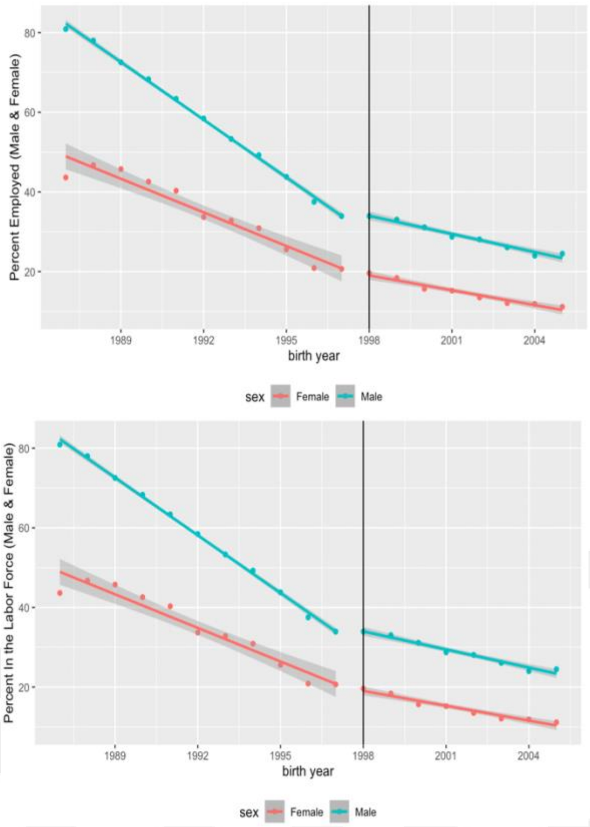


(b)

Note: Black vertical line passes through 1998 cut-off. First-order linear polynomials are fit to the left and right of the cut-off with 95% confidence interval. Panel (a) belongs to Sample A and panel (b) belongs to Sample B.

Figure 4.6 examines whether there is a discontinuous change in the outcome variables of employment and labor force participation status for females and males at the 1998 cut-off in Sample B. Upon visual inspection of these graphs, there is no apparent discontinuity at the cut-off value for the samples of both genders. Moreover, both employment and labor force participation percentages exhibit a downward trend across the birth cohorts considered.

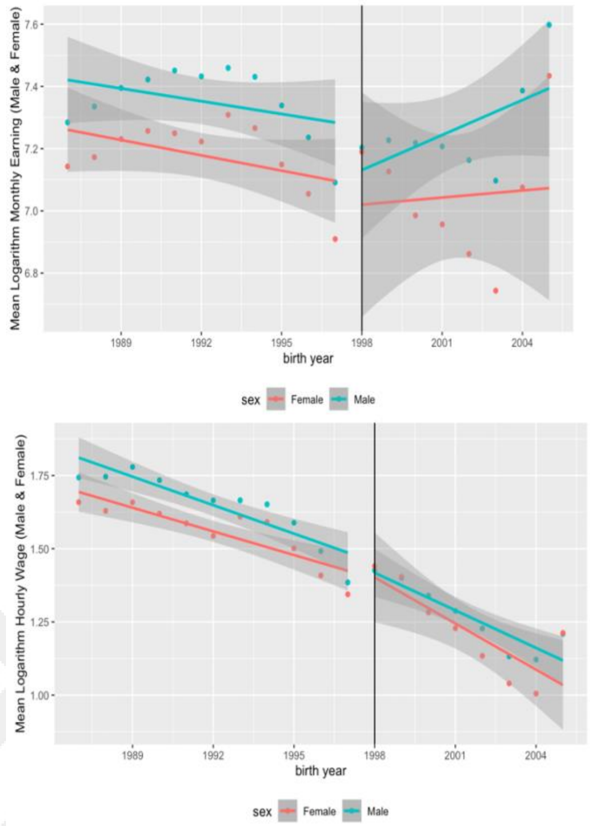
Figure 4.6. Fraction of Individuals Employed and in the Labor Force by Gender



Note: Black vertical line passes through 1998 cut-off. First-order linear polynomials are fit to the left and right of the cut-off with 95% confidence interval.

Figure 4.7 provides mean logarithm of income as well as mean logarithm of hourly wages by year of birth for treatment and control groups for females and males in sample A. As before, each point in the graph refers to average of logarithm of income (and to average of logarithm of hourly wages) for each birth cohort. It is observed in this figure that there is an upward jump in mean logarithm of monthly earnings of females and males after the policy implementation (i.e. at the cutoff) the slopes of the linear polynomials fitted to the left and right of the 1998 cutoff differ significantly, with the slope of the fit becoming steeper after the policy change. The change after the policy implementation is much clearer in mean logarithm of hourly wages. After a gradual decline, mean logarithm hourly wages exhibit an upward jump in 1998 and start a gradual increase after 1998 cutoff for both genders.

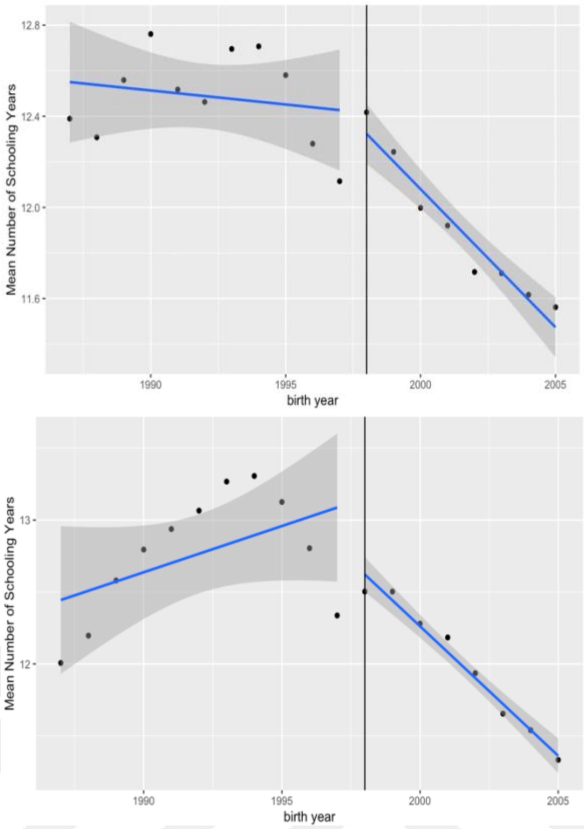
Figure 4.7. Mean Logarithm Income and Mean Logarithm Hourly Wage by Birth Year and by Gender



Note: Black vertical line passes through 1998 cut-off. First-order linear polynomials are fit to the left and right of the cut-off with 95% confidence interval.

Figure 4.8 depicts mean number of years of schooling by birth year for Sample A and Sample B. As before, each point in the graph refers to average number of schooling years for each birth cohort. In addition to the observed upward jump in the average number of schooling years attained for both samples, it is noteworthy that the volatility in mean schooling years attained is much smoother beyond the 1998 cutoff, indicating a similar pattern in both samples. Furthermore, the slopes of the linear polynomials fitted to the left and right of the 1998 cutoff differ apparently, with the declining slope of the fit becoming steeper after the policy change.

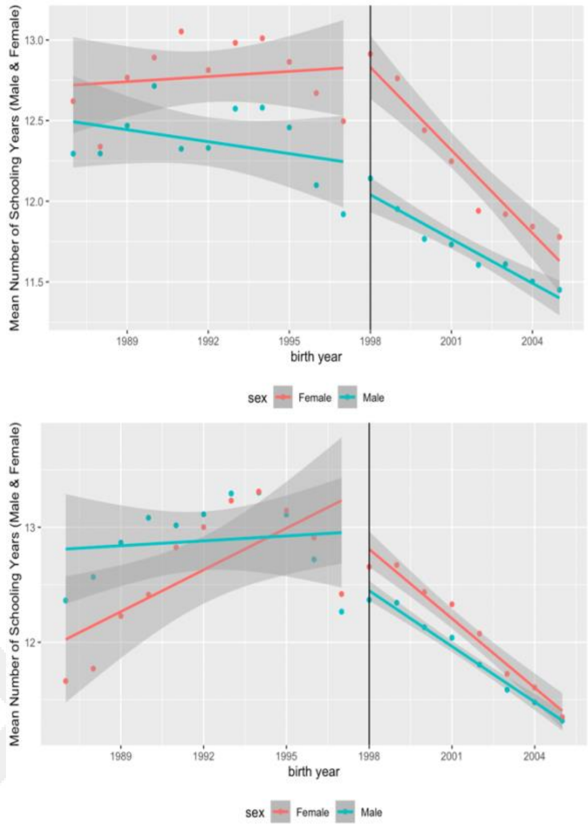
Figure 4.8. Mean Number of Schooling Years by Birth Year



Note: Black vertical line passes through 1998 cut-off. First-order linear polynomials are fit to the left and right of the cut-off with 95% confidence interval. Upper panel belongs to Sample A and lower panel belongs to Sample B.

Figure 4.9 replicates the same procedure in Figure 4.8 for females and males, separately. It is observed in this figure that there is an upward jump in mean number of years of schooling of females and males after the policy implementation (i.e. at the cutoff). Furthermore, the inference of declining volatility in mean number of years of schooling after 1998 cutoff also applies to both genders in both samples. Besides, after 1998 cutoff, there exists a clear downward trend in number of years of schooling attained for both genders in both samples. In all figures that plot average / percentage of indicated outcomes for females and males separately, the immediate upward jump at the cutoff point indicates that 2012 reform effectively raised proportion of individuals who are at least high school graduates. Therefore, based on the visual evidence, it is reasonable to anticipate an improvement in the outcome variables as a consequence of the 2012 reform.

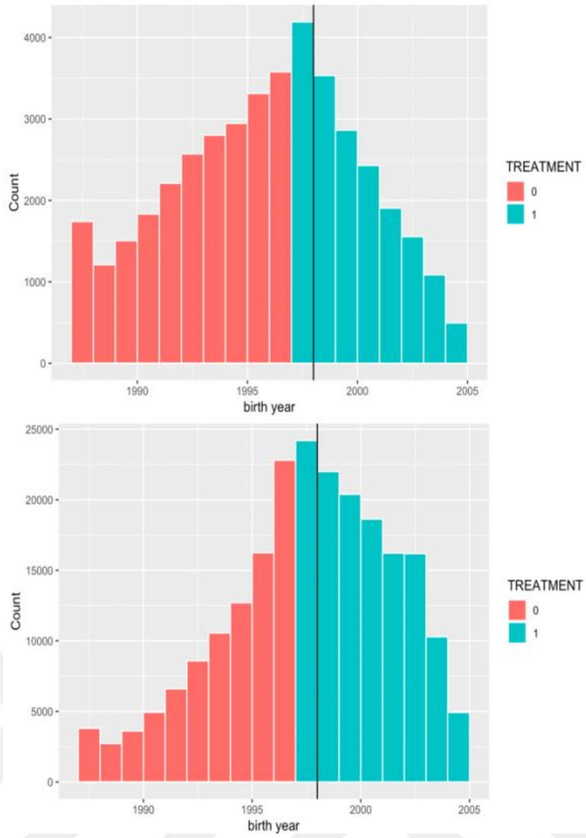
Figure 4.9. Mean Number of Schooling Years by Birth Year and by Gender



Note: Black vertical line passes through 1998 cut-off. First-order linear polynomials are fit to the left and right of the cut-off with 95% confidence interval. Upper panel belongs to Sample A and lower panel belongs to Sample B.

In the RDD setting, in order the running variable to be valid, individuals or researchers cannot be able to manipulate the treatment status or the cut-off value, hence individuals will be randomly assigned to the treatment. Possibility of manipulation in the running variable can be visually assessed through the density plot of the running variable (centered year of birth) which is depicted in Figure 4.10 for both of the samples. There appears to be no discontinuity or clustering in the distribution around the threshold, indicating the absence of manipulation. In addition to this, the p-values of the McCrary (2008) Density Test for manipulation are equal to 0.8704 and 0.5074 for Sample A and Sample B, respectively. This implies non-rejection of the null hypothesis of continuity of density of the running variable at conventional significance levels.

Figure 4.10. Density Distribution of Birth Year Variable



Note: Black vertical line passes through 1998 cut-off. Panel (a) belongs to Sample A, panel (b) belongs to Sample B.

4.5. Results

This section briefly presents the estimation results of the second stage regression in equation (4.3) and the first stage regression in equation (4.2), using three different definitions of the schooling variable: number of years of schooling attained, high school graduation status, and university graduation status; and four different outcome variables: logarithm of hourly wages, logarithm of income earned last month, employment status, and labor force participation status. In order to capture the effect of 2012 reform, all the models are run for individuals of age 17-30. There are two main subsamples Sample A and Sample B used in income and employment regressions, respectively. This is because in HLFS, income is reported for subjects who are employed only.

The tables in this section briefly present regression results according to the following structure: First the 2SLS estimations of the specified outcome and schooling variable are presented for males and females separately. Each column within these tables corresponds to estimates derived from polynomial degrees up to the 4th order in the centered birth year. The estimations are conducted using the maximum symmetric bandwidth around the 1998 cut-off and are subsequently reduced to lower symmetric bandwidths around this cut-off. Each column of these tables belong to the estimates from polynomial degrees up to 4th order in centered birth year. The first stage regression results which enable to evaluate effect of the policy on the specified educational outcome are given following tables of 2SLS regressions. Tables from 4.8 to 4.19 present first stage and second stage regressions that are run on Sample A which includes individuals who are employed only; and tables from 4.20 to 4.28 present the same that are run on Sample B which includes unemployed and out-of-labor force individuals as well as employed ones.

Table 4.8 briefly summarizes 2SLS estimation results of the effect of number of years of schooling attained on logarithm of monthly income. For the male sample, there exists no significant evidence in favor of positive effect of years of schooling attained on income. Besides, this is robust to bandwidth selection and the specification of the regression in terms of the polynomial degree of the centered birth year. For the female sample, there exist concrete evidence in favor of positive effect of years of schooling on income, and it is robust across different bandwidths and polynomial degree specifications. For females an additional year of schooling is expected to increase monthly income by 10.7% - 22%. According to Weak Identification Test statistics that are in the third row in each cell of Table 4.8, we reject the null hypothesis that instrumental variable is weak.

Table 4.8. The 2SLS Results of Logarithm of Monthly Income and Number of Years of Schooling

Polynomial Degree	First	Second	Third	Fourth
		Male		
BW7	-1.41	1.22	0.121	0.121
	(14.44)	(3.53)	(0.104)	(0.087)
	[0.012]	[0.146]	[32.312***]	[31.1***]
	{20857}	{20857}	{20857}	{20857}
BW5	0.28	0.268	0.051	0.0712
	(0.22)	(0.244)	(0.08)	(0.0544)
	[1.89]	[4.624**]	[22.334***]	[19.84***]
	{17425}	{17425}	{17425}	{17425}

Table 4.8.continued

Polynomial Degree	First	Second	Third	Fourth
BW3	0.13 (0.1) [4.91*] {12397}	0.116 (0.114) [6.934**] {12397}	0.039 (0.025) [20.518***] {12397}	0.125 (0.071) [85.026***] {12397}
		Female		
BW7	0.19*** (0.07) [5.87**] {8464}	0.21*** (0.057) [29.13***] {8464}	0.153*** (0.048) [33.952***] {8464}	0.151*** (0.0343) [24.873***] {8464}
BW5	0.22*** (0.06) [16.52***] {7284}	0.22*** (0.059) [26.79***] {7284}	0.079 (0.044) [17.882***] {7284}	0.107** (0.0341) [23.782***] {7284}
BW3	0.15*** (0.02) [42.71***] {5381}	0.152*** (0.032) [30.2***] {5381}	0.127*** (0.033) [22.644***] {5381}	0.044 (0.0348) [9.528**] {5381}

Note: Dependent variable is the logarithm of monthly income in each regression. Coefficient estimates belong to the effect of number of years of schooling variable. All regressions include controls for regional dummies of NUTS-1 level, age of the individual and survey year. The sample used for regression analysis is limited to individuals who were born in Türkiye and employed full-time. BW is the abbreviation for bandwidth. BW7 refers to maximum symmetric bandwidth of 7 years around 1998 cutoff. BW5 and BW3 refer to 5 and 3 years before and after 1998 cutoff, respectively. Standard errors are birth year-clustered and given in (). Weak IV Test statistics from each regression are presented in []. Number observations are given in {}. *** denotes significance at 1% level, ** denotes significance at 5% level, * denotes significance at 10% level.

Table 4.9 briefly summarizes the first stage estimation results related to the effect of the 2012 reform on the number of years of schooling attained in the regressions presented in Table 4.8. The table clearly indicates strong evidence of a positive and significant effect of the 2012 reform on the number of years of schooling attained, particularly for females. Furthermore, the significance of the effect remains robust across bandwidths and under different polynomial degrees of the centered birth year. For the male sample, coefficient estimates are strongly significant once higher order polynomials are introduced. Under each specification based on polynomial degree of the centered birth year except for linear and quadratic specifications with bandwidths of 5 and 7, those males who are affected by the reform are expected have 0.18- 0.41 more years of education than those who are not affected. The effect of reform is clearly higher for females and that it is robust to functional specification and different bandwidths. According to the results, those females who are affected by the reform are expected have 0.29- 0.62 more years of education than those who are not affected. Finally, greater than 10- first stage F statistics that are provided in the third row of each cell of Table 4.9 together with weak IV test results from Table 4.8, we can safely exclude the possibility of a weak IV problem in our results.

Table 4.9. The Policy Effect on Number of Years of Schooling

Polynomial Degree	First	Second	Third	Fourth
		Male		
BW7	-0.02	0.042	0.34***	0.339***
	(0.2)	(0.11)	(0.059)	(0.061)
	[165.2***]	[166.3***]	[160.1***]	[151.2***]
BW5	0.2	0.18**	0.39***	0.389***
	(0.14)	(0.083)	(0.082)	(0.0872)
	[194.3]	[184.7***]	[175.2***]	[165.4***]
BW3	0.31**	0.264***	0.412***	0.269***
	(0.14)	(0.1)	(0.091)	(0.0292)
	[202.2***]	[190***]	[179.2***]	[169.8***]
		Female		
BW7	0.4**	0.472***	0.62***	0.621***
	(0.16)	(0.087)	(0.11)	(0.125)
	[53.67***]	[56.81***]	[53.85***]	[50.92***]
BW5	0.52***	0.5***	0.61***	0.623***
	(0.13)	(0.097)	(0.143)	(0.128)
	[69***]	[67.32***]	[63.5***]	[60.02***]
BW3	0.5***	0.45***	0.391***	0.294***
	(0.07)	(0.082)	(0.082)	(0.095)
	[88.63***]	[83.18***]	[78.31***]	[74.06***]

Note: Coefficient estimates belong to the regression of number of years of schooling (SCH) on exposure to 2012 compulsory schooling law. The status of non-exposure to 2012 reform (where the value of CSL is equal to 0) is the reference category in each regression. All regressions include controls for regional dummies of NUTS-1 level, age of the individual and survey year. The sample used for regression analysis is limited to individuals who were born in Türkiye and employed full-time. BW is the abbreviation for bandwidth. BW7 refers to maximum symmetric bandwidth of 7 years around 1998 cutoff. BW5 and BW3 refer to 5 and 3 years before and after 1998 cutoff, respectively. Standard errors are birth year-clustered and are in (). First Stage F statistics are presented in [].*** denotes significance at 1% level, ** denotes significance at 5% level, * denotes significance at 10% level.

Table 4.10 presents the results that replicate the same procedure in Table 4.8 by employing high school graduation status instead of years of schooling as the schooling variable. For the male sample, the results imply that there exists no evidence in favor of return on having high school diploma and this effect is robust to bandwidth selection and functional form specification. For the female sample, the results imply that there exists strong evidence in favor of return on having high school diploma such that females who have high school degree are expected to have increase in their monthly income of magnitude between 35% (100*($e^{0.3} - 1$)%) and

86% (100*($e^{0.62} - 1$)%) with respect to those females who have below high school degree. According to Weak Identification Test statistics that are in the third row in each cell of Table 4.10, we reject the null hypothesis that instrumental variable is weak in the female sample. We also reject the null hypothesis that instrumental variable is weak for 2nd, 3rd, and 4th order specifications with bandwidth 7 and 5 and 4th order specifications with bandwidths 5 and 7 for the male sample.

Table 4.10. The 2SLS Results of Logarithm of Monthly Income and High school Graduation

Polynomial Degree	First	Second	Third	Fourth
		Male		
BW7	5.88	1.846	0.73	0.726
	(52.71)	(1.41)	(0.52)	(0.53)
	[0.01]	[2.613]	[6.015**]	[10.245***]
	{20857}	{20857}	{20857}	{20857}
BW5	1.135	1.155	0.42	0.51
	(0.72)	(0.815)	(0.65)	(0.48)
	[1.72]	[6.412**]	[5.425**]	[4.68**]
	{17425}	{17425}	{17425}	{17425}
BW3	0.891	0.892	0.37	3.42
	(0.833)	(1.13)	(0.695)	(3.734)
	[2.071]	[1.854]	[3.727]	[1.412]
	{12397}	{12397}	{12397}	{12397}
		Female		
BW7	0.477**	0.549***	0.516***	0.513***
	(0.186)	(0.112)	(0.127)	(0.12)
	[9.252***]	[30.091***]	[17.69***]	[31.7***]
	{8464}	{8464}	{8464}	{8464}
BW5	0.615***	0.606***	0.301*	0.382***
	(0.138)	(0.128)	(0.143)	(0.115)
	[29.04***]	[28.687***]	[14.83***]	[61.1***]
	{7284}	{7284}	{7284}	{7284}
BW3	0.47***	0.46***	0.319**	0.096
	(0.1)	(0.12)	(0.0976)	(0.086)
	[58.22***]	[52.402]	[68.19***]	[26.22***]
	{5381}	{5381}	{5381}	{5381}

Note: Dependent variable is the logarithm of monthly income in each regression. Coefficient estimates belong to the effect of being at least high school graduate. All regressions include controls for regional dummies of NUTS-1 level, age of the individual and survey year. The sample used for regression analysis is limited to individuals who were born in Türkiye and employed full-time. BW is the abbreviation for bandwidth. BW7 refers to maximum symmetric bandwidth of 7 years around 1998 cutoff. BW5 and BW3 refer to 5 and 3 years before and after 1998 cutoff, respectively. Standard errors are birth year-clustered and given in (). Weak IV Test statistics from each regression are presented in []. Number observations are given in {}. *** denotes significance at 1% level, ** denotes significance at 5% level, * denotes significance at 10% level.

The regression results presented in Table 4.11 investigate whether the positive significant effect of 2012 reform on years of schooling attained is translated into high school completion. The table provides evidence that the 2012 reform has positively and significantly impacted the high school graduation, especially among females. For the male sample, coefficient estimates are significant once higher order polynomials are introduced. Under each specification based on polynomial degree of the centered birth year except for linear specification with all bandwidths, those males who are affected by the reform are expected have 4.2 percentage points (pp.) – 5.6 pp. higher probability of having high school diploma with respect to those males who are not affected by the reform. Not only the effect of reform is clearly higher for females, but also it is robust to functional specification and different bandwidths. According to the results, those females who are affected by the reform are expected have 13.4 pp. – 18.6 pp. higher probability of graduating high school than those who are not affected. Finally, greater than 10- first stage F statistics that are provided in the third row of each cell of Table 4.11 together with weak IV test results from Table 4.10, we can safely exclude the possibility of a weak IV problem in our results.

Table 4.11. The Policy Effect on High school Completion

Polynomial Degree	**First**	**Second**	**Third**	**Fourth**
		Male		
BW7	0.0053	0.028	0.0564**	0.056***
	(0.054)	(0.0172)	(0.023)	(0.0176)
	[153.9***]	[168.3***]	[158.9***]	[150.8***]
BW5	0.049	0.0415**	0.047**	0.0547**
	(0.037)	(0.0164)	(0.02)	(0.0253)
	[169.1***]	[163.4***]	[153.8***]	[145.6***]
BW3	0.046	0.034	0.045*	9.8×10^{-3}
	(0.032)	(0.025)	(0.0233)	(8.3×10^{-3})
	[169.7***]	[159.5***]	[150.2***]	[142.3***]
		Female		
BW7	0.149***	0.18***	0.184***	0.183***
	(0.049)	(0.033)	(0.044)	(0.033)
	[54.8***]	[65.82***]	[61.94***]	[58.8***]
BW5	0.186***	0.181***	0.158***	0.174***
	(0.035)	(0.034)	(0.041)	(0.022)
	[65.67***]	[64.88***]	[61.2***]	[58.52***]
BW3	0.151***	0.15***	0.155***	0.134***
	(0.02)	(0.021)	(0.019)	(0.0262)
	[72.1***]	[67.59***]	[63.6***]	[60.14***]

Note: Coefficient estimates belong to the regression of at least high school graduation on exposure to 2012 compulsory schooling law. The status of non-exposure to 2012 reform (where the value of CSL is equal to 0) is the reference category in each regression. All regressions include controls for regional dummies of NUTS-1 level, age of the individual and survey year. The sample used for regression analysis is limited to individuals who were born in Türkiye and employed full-time. BW is the abbreviation for bandwidth. BW7 refers to maximum symmetric bandwidth of 7 years around 1998 cutoff. BW5 and BW3 refer to 5 and 3 years before and after 1998 cutoff, respectively. Standard errors are birth year-clustered and are in (). First Stage F statistics are presented in [].*** denotes significance at 1% level, ** denotes significance at 5% level, * denotes significance at 10% level.

Table 4.12 presents the results that replicate the same procedures in Tables 4.8 and 4.10 by employing university graduation status instead of years of schooling and high school graduation status as the schooling variable. According to results, the return on university graduation is only significant under quartic specification for those males who were born 3 years around 1998: 22.1% (100*($e^{0.2}-1$)%) increase in their monthly income. For the female sample, however, the return on university diploma is strongly significant and positive: females who have university degree are expected to have increase in their monthly income of magnitude between 13% (100*($e^{0.125}-1$)%) and 39% (100*($e^{0.33}-1$)%) with respect to those females who have below university degree.

Table 4.12. The 2SLS Results of Logarithm of Monthly Income and University Graduation

Polynomial Degree	First	Second	Third	Fourth
		Male		
BW7	0.11	0.195	0.227*	0.154
	(0.135)	(0.17)	(0.116)	(0.15)
	[54.66***]	[95.832***]	[733.03***]	[537.4***]
	{12263}	{12263}	{12263}	{12263}
BW5	0.244	0.167	0.21	0.0625
	(0.15)	(0.12)	(0.131)	(0.109)
	[44.372***]	[287.3***]	[1144.7***]	[547.5***]
	{9349}	{9349}	{9349}	{9349}
BW3	0.192	0.193	0.071	0.201***
	(0.16)	(0.11)	(0.148)	(0.04)
	[33.77***]	[978.6***]	[413.37***]	[588.7***]
	{5892}	{5892}	{5892}	{5892}
		Female		
BW7	0.189*	0.27**	0.317***	0.333***
	(0.093)	(0.094)	(0.069)	(0.088)
	[51.87***]	[101.693***]	[255.15***]	[147.9***]
	{5383}	{5383}	{5383}	{5383}
BW5	0.328***	0.271***	0.333***	0.241***
	(0.092)	(0.051)	(0.08)	(0.06)
	[41.044***]	[226.66***]	[196.64***]	[504.98***]
	{4345}	{4345}	{4345}	{4345}

Table 4.12.continued

Polynomial Degree	First	Second	Third	Fourth
BW3	0.268*** (0.06) [43.74***] {2975}	0.278*** (0.048) [409.9***] {2975}	0.191*** (0.041) [428.65***] {2975}	0.125** (0.035) [3274.4***] {2975}

Note: Dependent variable is the logarithm of monthly income in each regression. Coefficient estimates belong to the effect of being at least university graduate. All regressions include controls for regional dummies of NUTS-1 level, age of the individual and survey year. The sample used for regression analysis is limited to individuals who were born in Türkiye and employed full-time. BW is the abbreviation for bandwidth. BW7 refers to maximum symmetric bandwidth of 7 years around 1998 cutoff. BW5 and BW3 refer to 5 and 3 years before and after 1998 cutoff, respectively. Standard errors are birth year-clustered and given in (). Weak IV Test statistics from each regression are presented in []. Number observations are given in {}. *** denotes significance at 1% level, ** denotes significance at 5% level, * denotes significance at 10% level.

According to the results in table 4.13, the gains in years of education and high school degree attainment have been translated into university degree attainment particularly for females. For the male sample, across all bandwidths and under all functional forms, there is strong and significant positive evidence of the impact of the 2012 reform. The magnitude of such an effect ranges between 16.5 pp. and 23 pp. The evidence related to the impact of the reform on university degree attainment of females is statistically significant for all bandwidths under all specifications: females who are subject to the new law are expected to complete university with 36 pp. – 49 pp. higher probability. Finally, greater than 10- first stage F statistics that are provided in the third row of each cell of Table 4.13 together with weak IV test results in Male panel of Table 4.12 , we can safely exclude the possibility of a weak IV problem in the results related to male sample. Weak IV test statistics in the female panel of Table 4.12 indicate that exposure to 2012 compulsory schooling law may not be a good instrument for university degree attainment in the female sample.

Table 4.13. The Policy Effect on University Completion

Polynomial Degree	First	Second	Third	Fourth
		Male		
BW7	0.165*** (0.022) [123.4***]	0.224*** (0.023) [124.5***]	0.217*** (0.008) [121.1***]	0.21*** (0.009) [114.4***]
BW5	0.179*** (0.027) [89.17***]	0.23*** (0.0136) [91.58***]	0.21*** (0.0062) [87.25***]	0.216 (0.0092) [82.47***]

Table 4.13.continued

Polynomial Degree	First	Second	Third	Fourth
BW3	0.219*** (0.038) [49.81***]	0.218*** (0.007) [50.36***]	0.214*** (0.011) [47.4***]	0.205*** (0.0084) [44.9***]
		Female		
BW7	0.36*** (0.05) [138.7***]	0.462*** (0.046) [138.8***]	0.44*** (0.028) [132.7***]	0.47*** (0.039) [125.6***]
BW5	0.386*** (0.06) [104.9***]	0.464*** (0.031) [105.8***]	0.447*** (0.032) [99.75***]	0.49*** (0.022) [95.24***]
BW3	0.459*** (0.07) [61.99***]	0.443 (0.022) [60.69***]	0.49*** (0.024) [57.47***]	0.458*** (0.008) [54.56***]

Note: Coefficient estimates belong to the regression of university graduation status on exposure to 2012 compulsory schooling law. The status of non-exposure to 2012 reform (where the value of CSL is equal to 0) is the reference category in each regression. All regressions include controls for regional dummies of NUTS-1 level, age of the individual and survey year. The sample used for regression analysis is limited to individuals who were born in Türkiye and employed full-time. BW is the abbreviation for bandwidth. BW7 refers to maximum symmetric bandwidth of 7 years around 1998 cutoff. BW5 and BW3 refer to 5 and 3 years before and after 1998 cutoff, respectively. Standard errors are birth year-clustered and are in (). First Stage F statistics are presented in [].*** denotes significance at 1% level, ** denotes significance at 5% level, * denotes significance at 10% level.

Table 4.14 briefly summarizes 2SLS estimation results of the effect of number of years of schooling attained on logarithm of hourly wage. For the male sample, there exists significant evidence in favor of positive effect of years of schooling attained on hourly wage yet the effect is not robust to functional form specification. For the female sample, there exists evidence in favor of positive effect of years of schooling on hourly wage, and it is robust to different bandwidths and different functional forms. For males, an additional year of schooling is associated with 12% - 16% increase in hourly wage whereas for females an additional year of schooling is expected to increase hourly wage by 10% - 20%. According to Weak Identification Test statistics that are in the third row of each cell of Table 4.14, we reject the null hypothesis that instrumental variable is weak.

Table 4.14. The 2SLS Results of Logarithm of Hourly Wage and Number of Years of Schooling

Polynomial Degree	First	Second	Third	Fourth
		Male		
BW7	-0.67	0.753	0.14*	0.14*
	(7.67)	(2.02)	(0.073)	(0.068)
	[0.012]	[0.146]	[32.31***]	[31.1***]
	{20857}	{20857}	{20857}	{20857}
BW5	0.226	0.216	0.102	0.121**
	(0.144)	(0.161)	(0.067)	(0.044)
	[1.89]	[4.624**]	[22.334***]	[19.84***]
	{17425}	{17425}	{17425}	{17425}
BW3	0.149	0.142	0.09	0.16**
	(0.077)	(0.089)	(0.052)	(0.055)
	[4.192*]	[6.934**]	[20.52***]	[85.026***]
	{12397}	{12397}	{12397}	{12397}
		Female		
BW7	0.161**	0.18***	0.153***	0.152***
	(0.06)	(0.05)	(0.041)	(0.031)
	[5.87**]	[29.13***]	[33.95***]	[24.9***]
	{8464}	{8464}	{8464}	
BW5	0.2***	0.2***	0.0988**	0.117***
	(0.047)	(0.05)	(0.032)	(0.027)
	[16.52***]	[26.8***]	[17.882***]	[23.8***]
	{7284}	{7284}	{7284}	{7284}
BW3	0.144***	0.143***	0.115***	0.031
	(0.021)	(0.026)	(0.03)	(0.055)
	[42.71***]	[30.2***]	[22.64***]	[9.528**]
	{5381}	{5381}	{5381}	{5381}

Note: Dependent variable is the logarithm of hourly wage in each regression. Coefficient estimates belong to the effect of number of years of schooling variable. All regressions include controls for regional dummies of NUTS-1 level, age of the individual and survey year. The sample used for regression analysis is limited to individuals who were born in Türkiye and employed full-time. BW is the abbreviation for bandwidth. BW7 refers to maximum symmetric bandwidth of 7 years around 1998 cutoff. BW5 and BW3 refer to 5 and 3 years before and after 1998 cutoff, respectively. Standard errors are birth year-clustered and given in (). Weak IV Test statistics from each regression are presented in []. Number observations are given in {}. *** denotes significance at 1% level, ** denotes significance at 5% level, * denotes significance at 10% level.

Table 4.15 briefly summarizes the first stage estimation results related to the effect of the 2012 reform on the number of years of schooling attained in the regressions presented in Table 4.14. It is clear from the table that there exists strong evidence in favor of positive significant effect of 2012 reform on the number of years of schooling attained particularly for females and occasionally for males. Furthermore, the significance of the effect remains robust across bandwidths and under different polynomial degrees of the centered birth year. For the male sample, coefficient estimates are strongly significant once higher order polynomials are introduced. Under each specification based on polynomial degree of the centered birth year except for linear and quadratic specifications with bandwidths of 5 and 7, those males who are affected by the reform are expected have 0.18- 0.41 more years of education than those who are not affected. The effect of reform is clearly higher for females and that it is robust to functional specification and different bandwidths. According to the results, those females who are affected by the reform are expected have 0.29- 0.62 more years of education than those who are not affected. It is worthy to note that these estimates are quite close to the estimates in Table 3.9 which presented first stage regression of years of schooling on exposure to compulsory schooling law status for the income sample. Finally, greater than 10 - first stage F statistics that are provided in the third row of each cell of Table 4.15 together with weak IV test results from Table 4.14, we can safely exclude the possibility of a weak IV problem in our results.

Table 4.15. The Policy Effect on Number of Years of Schooling

Polynomial Degree	**First**	**Second**	**Third**	**Fourth**
		Male		
BW7	-0.022	0.042	0.34***	0.34***
	(0.203)	(0.11)	(0.059)	(0.061)
	[165.2***]	[166.3***]	[160.1***]	[151.2***]
BW5	0.2	0.179**	0.386***	0.39***
	(0.146)	(0.083)	(0.082)	(0.087)
	[194.3***]	[184.7***]	[175.2***]	[165.4***]
BW3	0.31**	0.264***	0.412***	0.269***
	(0.14)	(0.1)	(0.091)	(0.029)
	[202.2***]	[190***]	[179.2***]	[169.8***]
		Female		
BW7	0.384**	0.47***	0.62***	0.621***
	(0.159)	(0.088)	(0.11)	(0.125)
	[53.7***]	[56.8***]	[53.85***]	[50.92***]
BW5	0.52***	0.5***	0.61***	0.623***
	(0.128)	(0.09)	(0.143)	(0.13)
	[69***]	[67.32***]	[63.5***]	[60.02***]
BW3	0.486***	0.452**	0.391***	0.294***
	(0.074)	(0.104)	(0.082)	(0.095)
	[88.63***]	[83.18***]	[78.31***]	[74.06***]

Note: Coefficient estimates belong to the regression of number of years of schooling (SCH) on exposure to 2012 compulsory schooling law. The status of non-exposure to 2012 reform (where the value of CSL is equal to 0) is the reference category in each regression. All regressions include controls for regional dummies of NUTS-1 level, age of the individual and survey year. The sample used for regression analysis is limited to individuals who were born in Türkiye and employed full-time. BW is the abbreviation for bandwidth. BW7 refers to maximum symmetric bandwidth of 7 years around 1998 cutoff. BW5 and BW3 refer to 5 and 3 years before and after 1998 cutoff, respectively. Standard errors are birth year-clustered and are in (). First Stage F statistics are presented in [].*** denotes significance at 1% level, ** denotes significance at 5% level, * denotes significance at 10% level.

Table 4.16 presents the results that replicate the same procedure in Table 4.14 by employing high school graduation status instead of years of schooling as the schooling variable. For the male sample, the results imply that there exists no evidence in favor of return on having high school diploma and this is robust to different bandwidths or functional form specifications. Besides, Weak IV test statistics that are in the third row of each cell in Table 16 imply that estimates for the male sample may suffer from weak IV problem. For the female sample, the results imply that there exists strong significant evidence in favor of return on having high school diploma such that females who have high school degree are expected to have increase in their hourly wage of magnitude between 34% (100*($e^{0.29} - 1$)%) and 75% (100*($e^{0.56} - 1$)%) with respect to those females who have below high school degree. According to Weak Identification Test statistics that are in the third row in each cell of Table 4.16, we reject the null hypothesis that instrumental variable is weak in the female sample.

Table 4.16. The 2SLS Results of Logarithm of Hourly Wage and High school Graduation

Polynomial Degree	First	Second	Third	Fourth
		Male		
BW7	2.78	1.14	0.84**	0.841*
	(21.58)	(0.78)	(0.38)	(0.43)
	[0.01]	[2.613]	[6.015**]	[10.25***]
	{20857}	{20857}	{20857}	{20857}
BW5	0.927*	0.93	0.842	0.855
	(0.476)	(0.57)	(0.56)	(0.484)
	[1.72]	[6.412**]	[5.425**]	[4.677**]
	{17425}	{17425}	{17425}	{17425}
BW3	0.998	1.09	0.824	4.38
	(0.72)	(1.004)	(0.71)	(4.12)
	[2.071]	[1.854]	[3.73]	[1.412]
	{12397}	{12397}	{12397}	{12397}
		Female		
BW7	0.415**	0.47***	0.515***	0.514***
	(0.15)	(0.099)	(0.12)	(0.12)
	[9.25***]	[30.1***]	[17.69***]	[31.69***]
	{8464}	{8464}		{8464}

Table 4.16.continued

Polynomial Degree	**First**	**Second**	**Third**	**Fourth**
BW5	0.557***	0.552***	0.38***	0.42***
	(0.111)	(0.11)	(0.11)	(0.11)
	[29.04***]	[28.7***]	[14.83***]	[61.094***]
	{7284}	{7284}	{7284}	{7284}
BW3	0.462***	0.43***	0.291**	0.068
	(0.105)	(0.11)	(0.104)	(0.13)
	[58.22***]	[52.4***]	[68.19***]	[26.22***]
	{5381}	{5381}	{5381}	{5381}

Note: Dependent variable is the logarithm of monthly income in each regression. Coefficient estimates belong to the effect of being at least high school graduate. All regressions include controls for regional dummies of NUTS-1 level, age of the individual and survey year. The sample used for regression analysis is limited to individuals who were born in Türkiye and employed full-time. BW is the abbreviation for bandwidth. BW7 refers to maximum symmetric bandwidth of 7 years around 1998 cutoff. BW5 and BW3 refer to 5 and 3 years before and after 1998 cutoff, respectively. Standard errors are birth year-clustered and given in (). Weak IV Test statistics from each regression are presented in []. Number observations are given in {}. *** denotes significance at 1% level, ** denotes significance at 5% level, * denotes significance at 10% level.

The regression results presented in Table 4.17 investigate whether the positive significant effect of 2012 reform on years of schooling attained is translated into high school completion. The table provides evidence that the 2012 reform has positively and significantly impacted the high school graduation, especially among females. For the male sample, coefficient estimates are significant once higher order polynomials are introduced. Under each specification based on polynomial degree of the centered birth year except for linear functional form and quadratic specification with bandwidth 5, those males who are affected by the reform are expected have 4.1 percentage points (pp.) – 5.6 pp. higher probability of having high school diploma with respect to those males who are not affected by the reform. Although the effect of reform is clearly higher for females, it is robust to functional specification and different bandwidths. According to the results, those females who are affected by the reform are expected have 13.4 pp. – 18.6 pp. higher probability of graduating high school than those who are not affected. Finally, greater than 10- first stage F statistics that are provided in the third row of each cell of Table 4.17 together with weak IV test results from Table 4.16, we can safely exclude the possibility of a weak IV problem in our results.

Table 4.17. The Policy Effect on High school Completion

Polynomial Degree	First	Second	Third	Fourth
		Male		
BW7	0.005	0.028	0.056**	0.0563***
	(0.054)	(0.017)	(0.023)	(0.018)
	[153.9***]	[168.3***]	[158.9***]	[150.8***]
BW5	0.049	0.041**	0.047**	0.0547**
	(0.037)	(0.016)	(0.02)	(0.0253)
	[169.1***]	[163.4***]	[153.8***]	[145.6***]
BW3	0.046	0.034	0.045**	0.0098
	(0.032)	(0.025)	(0.023)	(0.0083)
	[169.7***]	[159.5***]	[150.2***]	[142.3***]
		Female		
BW7	0.149***	0.18***	0.184***	0.183***
	(0.049)	(0.033)	(0.044)	(0.033)
	[54.79***]	[65.82***]	[61.94***]	[58.8***]
BW5	0.186***	0.181***	0.158***	0.174***
	(0.035)	(0.034)	(0.041)	(0.022)
	[65.67***]	[64.88***]	[61.2***]	[58.52***]
BW3	0.151***	0.15***	0.155***	0.134***
	(0.019)	(0.017)	(0.019)	(0.0262)
	[72.1***]	[67.6***]	[63.6***]	[60.14***]

Note: Coefficient estimates belong to the regression of at least high school graduation on exposure to 2012 compulsory schooling law. The status of non-exposure to 2012 reform (where the value of CSL is equal to 0) is the reference category in each regression. All regressions include controls for regional dummies of NUTS-1 level, age of the individual and survey year. The sample used for regression analysis is limited to individuals who were born in Türkiye and employed full-time. BW is the abbreviation for bandwidth. BW7 refers to maximum symmetric bandwidth of 7 years around 1998 cutoff. BW5 and BW3 refer to 5 and 3 years before and after 1998 cutoff, respectively. Standard errors are birth year-clustered and are in (). First Stage F statistics are presented in [].*** denotes significance at 1% level, ** denotes significance at 5% level, * denotes significance at 10% level.

Table 4.18 presents the results that replicate the same procedures in Tables 4.14 and 4.16 by employing university graduation status instead of years of schooling and high school graduation status as the schooling variable. In contrast to previous findings related to returns on years of schooling and high school graduation for the male sample, the effect of having university diploma as a result of 2012 reform on hourly wage is significantly positive depending on bandwidth and functional form specification. For example; under linear and quadratic functional specifications, those males who were born 3 years around 1998 are expected to have 45% (100*($e^{0.37}-1$)%) and 46% (100*($e^{0.38}-1$)%) increase in their hourly wage. Under quartic functional form, such an effect is about 52%-53% increment for males. For females, the return on having university diploma as a result of 2012 reform on hourly wage is significantly positive yet this effect isn't as strong as previous findings. The magnitude of the effect ranges between 16% (100*($e^{0.15} - 1$)%) and 48% (100*($e^{0.39} - 1$)%). According to Weak Identification Test statistics that are in the third row in each cell of Table 4.18, we reject the null hypothesis that instrumental variable is weak in both samples.

Table 4.18. The 2SLS Results of Logarithm of Hourly Wage and University Graduation

Polynomial Degree	First	Second	Third	Fourth
		Male		
BW7	0.168	0.334*	0.433	0.432**
	(0.413)	(0.19)	(0.259)	(0.184)
	[9.8***]	[43.86***]	[31.64***]	[193.2***]
	{20857}	{20857}	{20857}	{20857}
BW5	0.441*	0.39*	0.339	0.432***
	(0.198)	(0.185)	(0.23)	(0.11)
	[11.69***]	[82.2***]	[58.8***]	[525.7***]
	{17425}	{17425}	{17425}	{17425}
BW3	0.383***	0.37**	0.324*	0.42**
	(0.097)	(0.12)	(0.14)	(0.123)
	[19.55***]	[321.8***]	[328.6***]	[397.94***]
	{12397}	{12397}	{12397}	{12397}
		Female		
BW7	0.27*	0.34**	0.325*	0.321
	(0.13)	(0.14)	(0.163)	(0.00193)
	[13.214***]	[58.02***]	[40.43***]	[190.9***]
	{8464}	{8464}	{8464}	{8464}
BW5	0.39**	0.385**	0.192	0.247***
	(0.13)	(0.14)	(0.107)	(0.076)
	[15.47***]	[93.14***]	[75.3***]	[327.91***]
	{7284}	{7284}	{7284}	{7284}
BW3	0.225**	0.24***	0.145**	0.033
	(0.065)	(0.017)	(0.056)	(0.067)
	[31.3***]	[182.9***]	[344.8***]	[218.16***]
	{5381}	{5381}	{5381}	{5381}

Note: Dependent variable is the logarithm of hourly wage in each regression. Coefficient estimates belong to the effect of being at least university graduate. All regressions include controls for regional dummies of NUTS-1 level, age of the individual and survey year. The sample used for regression analysis is limited to individuals who were born in Türkiye and employed full-time. BW is the abbreviation for bandwidth. BW7 refers to maximum symmetric bandwidth of 7 years around 1998 cutoff. BW5 and BW3 refer to 5 and 3 years before and after 1998 cutoff, respectively. Standard errors are birth year-clustered and given in (). Weak IV Test statistics from each regression are presented in []. Number observations are given in {}. *** denotes significance at 1% level, ** denotes significance at 5% level, * denotes significance at 10% level.

According to the results in table 4.19, the gains in years of education and high school degree attainment have been translated into university degree attainment. For both samples, there exist strong significant evidence on the positive effect of exposure to 2012 reform on university completion. And this result is robust to different bandwidths as well as different polynomial orders of centered birth year. For example among those males who are subject to the new policy are expected to have university diploma by 8.7 pp. – 12 pp. higher probability. Such an effect is clearly higher for females and it ranges between 23 pp. – 31 pp. Finally, greater than 10-first stage F statistics that are provided in the third row of each cell of Table 4.19 together with weak IV test results in Table 4.18 , we can safely exclude the possibility of a weak IV problem in the results related to both samples.

Table 4.19. The Policy Effect on University Completion

Polynomial Degree	**First**	**Second**	**Third**	**Fourth**
		Male		
BW7	0.087***	0.095***	0.11***	0.11***
	(0.028)	(0.014)	(0.02)	(0.0079)
	[79.61***]	[100.8***]	[96.66***]	[98.89***]
BW5	0.103***	0.098***	0.116***	0.11***
	(0.03)	(0.01)	(0.015)	(0.0048)
	[75.84***]	[90.21***]	[86.51***]	[85***]
BW3	0.12***	0.101***	0.114***	0.102***
	(0.027)	(0.005)	(0.0063)	(0.0051)
	[64.9***]	[68.04***]	[64.38***]	[61.2***]
		Female		
BW7	0.231***	0.251***	0.291***	0.294***
	(0.064)	(0.033)	(0.046)	(0.0213)
	[102.1***]	[125.2***]	[120.6***]	[122.8***]
BW5	0.27***	0.26***	0.312***	0.296***
	(0.068)	(0.027)	(0.036)	(0.0163)
	[97.52***]	[113.4***]	[109.4***]	[106.7***]
BW3	0.31***	0.27***	0.312***	0.28***
	(0.05)	(0.02)	(0.017)	(0.019)
	[84.4***]	[86.13***]	[81.93***]	[78.1***]

Note: Coefficient estimates belong to the regression of university graduation status on exposure to 2012 compulsory schooling law. The status of non-exposure to 2012 reform (where the value of CSL is equal to 0) is the reference category in each regression. All regressions include controls for regional dummies of NUTS-1 level, age of the individual and survey year. The sample used for regression analysis is limited to individuals who were born in Türkiye and employed full-time. BW is the abbreviation for bandwidth. BW7 refers to maximum symmetric bandwidth of 7 years around 1998 cutoff. BW5 and BW3 refer to 5 and 3 years before and after 1998 cutoff, respectively. Standard errors are birth year-clustered and are in (). First Stage F statistics are presented in []. *** denotes significance at 1% level, ** denotes significance at 5% level, * denotes significance at 10% level.

Tables from 4.20 to 4.28 present first stage and second stage regressions that are run on Sample B which includes individuals who are employed as well as either unemployed or out of labor force. Table 4.20 briefly summarizes 2SLS estimation results of the effect of number of years of schooling attained on employment status. For male sample, there exist no evidence in favor of the effect of years of schooling on employment probabilities, this effect is found to be robust to bandwidth selection and functional form specification. For female sample, there exist significant evidence in favor of the effect of schooling on employment probability yet such an effect is not robust to either bandwidth selection or functional form specification. An additional year of education for females born within three years of 1998, due to the 2012 compulsory schooling reform, leads to a 16% higher probability of employment. Based on Weak IV Test statistics that are provided in the third row of each cell in the female panel of Table 4.20, we can safely reject the possibility of weak instruments problem in this result.

Table 4.20. The 2SLS Results of Employment Status and Number of Years of Schooling

Polynomial Degree	First	Second	Third	Fourth
		Male		
BW7	0.75	-0.23	0.193	0.115
	(0.901)	(0.19)	(0.234)	(0.069)
	[0.036]	[1.265]	[0.811]	[4.147*]
	{113057}	{113057}	{113057}	{113057}
BW5	0.14	1.09	0.25	0.147*
	(0.13)	(3.26)	(0.195)	(0.07)
	[2.4]	[0.112]	[1.601]	[6.165**]
	{98828}	{98828}	{98828}	{98828}
BW3	0.211*	0.318	0.245*	0.569
	(0.101)	(0.19)	(0.121)	(0.579)
	[12.29**]	[4.412*]	[4.864*]	[0.935]
	{71696}	{71696}	{71696}	{71696}
		Female		
BW7	0.07	-0.084	0.185	0.101
	(0.057)	(0.086)	(0.292)	(0.081)
	[0.815]	[0.777]	[0.546]	[2.456]
	{99329}	{99329}	{99329}	{99329}
BW5	0.084*	1.763	0.235	0.094
	(0.042)	(21.4)	(0.488)	(0.0553)
	[2.38]	[0.007]	[0.71]	[4.274*]
	{87226}	{87226}	{87226}	{87226}

Table 4.20.continued

Polynomial Degree	First	Second	Third	Fourth
BW3	0.16*** (0.04) [6.573**] {63589}	0.255 (0.261) [1.269] {63589}	0.354 (0.305) [1.336] {63589}	0.241 (0.325) [0.511] {63589}

Note: Dependent variable is the employment status in each regression. Coefficient estimates belong to the effect of number of years of schooling variable. All regressions include controls for regional dummies of NUTS-1 level, age of the individual and survey year. The sample used for regression analysis is limited to individuals who were born in Türkiye. BW is the abbreviation for bandwidth. BW7 refers to maximum symmetric bandwidth of 7 years around 1998 cutoff. BW5 and BW3 refer to 5 and 3 years before and after 1998 cutoff, respectively. Standard errors are birth year-clustered and given in (). Weak IV Test statistics from each regression are presented in []. Number observations are given in {}. *** denotes significance at 1% level, ** denotes significance at 5% level, * denotes significance at 10% level.

Table 4.21 briefly summarizes the first stage estimation results related to the effect of the 2012 reform on the number of years of schooling attained in the regressions presented in Table 4.20. Sample B which consists of unemployed and out of labor force individuals in addition to employed individuals does not produce evidence as strong as in Sample A which consists of employed individuals only and the coefficient estimates are much smaller comparably. It is clear from the table that empirical evidence related to the effect of being exposed to 2012 reform on number of years of schooling attained is sensitive to different bandwidths and polynomial degree in centered birth year. According to quartic functional specification results, for males who were born 7 and 5 years around 1998, those who were affected by the reform are expected to have 0.18 more years of schooling than those who are not affected. The effect of reform is slightly higher for females such that those who were born 5 years before and after 1998 cut-off and affected by the reform are expected to have 0.19 more years of schooling than those females who are not affected. According to linear functional specification results, for males who were born 3 years around 1998, those who were affected by the reform are expected to have 0.12 more years of schooling than those who are not affected. The effect of reform is only slightly higher for females such that those who were born 3 years around 1998 cut-off and affected by the reform are expected to have 0.15 more years of schooling than those females who are not affected. Considering that some of the coefficients are insignificant and insignificant Weak IV Test Statistics at different bandwidths, there may exist weak IV problem in these results although first stage F statistics are greater than 10 as provided in the third row of each cell of Table 4.21.

Table 4.21. The Policy Effect on Number of Years of Schooling

Polynomial Degree	First	Second	Third	Fourth
		Male		
BW7	0.029	-0.123	0.117	0.181**
	(0.15)	(0.11)	(0.131)	(0.088)
	[1922***]	[1938***]	[1849***]	[1755***]
BW5	0.12	0.021	0.111	0.176**
	(0.081)	(0.061)	(0.088)	(0.071)
	[2124***]	[2019***]	[1904***]	[1802***]
BW3	0.121***	0.086**	0.0978**	0.0628
	(0.035)	(0.041)	(0.044)	(0.0649)
	[1984***]	[1861***]	[1752***]	[1655***]
		Female		
BW7	0.18	-0.11	0.114	0.189
	(0.20)	(0.12)	(0.155)	(0.121)
	[1465***]	[1617***]	[1542***]	[1464***]
BW5	0.21	0.0076	0.0963	0.19**
	(0.11)	(0.09)	(0.115)	(0.092)
	[1788***]	[1746***]	[1646***]	[1560***]
BW3	0.145**	0.065	0.0693	0.0652
	(0.058)	(0.058)	(0.059)	(0.091)
	[1903***]	[1789***]	[1684***]	[1590***]

Note: Coefficient estimates belong to the regression of number of years of schooling (SCH) on exposure to 2012 compulsory schooling law. The status of non-exposure to 2012 reform (where the value of CSL is equal to 0) is the reference category in each regression. All regressions include controls for regional dummies of NUTS-1 level, age of the individual and survey year. The sample used for regression analysis is limited to individuals who were born in Türkiye. BW is the abbreviation for bandwidth. BW7 refers to maximum symmetric bandwidth of 7 years around 1998 cutoff. BW5 and BW3 refer to 5 and 3 years before and after 1998 cutoff, respectively. Standard errors are birth year-clustered and are in (). First Stage F statistics are presented in [].*** denotes significance at 1% level, ** denotes significance at 5% level, * denotes significance at 10% level.

Table 4.22. The 2SLS Results of Employment Status and High school Completion

Polynomial Degree	First	Second	Third	Fourth
		Male		
BW7	0.821	-0.82	-268.6	0.86
	(1.92)	(0.44)	(1.9×10^5)	(1.51)
	[0.236]	[0.61]	[0]	[0.332]
	{113057}	{113057}	{113057}	{113057}
BW5	0.45	-4.13	-1.38	0.759
	(0.54)	(29.48)	(3.44)	(0.447)
	[1.09]	[0.02]	[0.162]	[3.961*]
	{98828}	{98828}	{98828}	{98828}

Table 4.22.continued

Polynomial Degree	**First**	**Second**	**Third**	**Fourth**
BW3	7.85 (33.61) [0.051] {71696}	2.043 (2.28) [0.922] {71696}	0.962* (0.455) [3.358] {71696}	1.217 (0.871) [1.952] {71696}
			Female		
BW7	0.169 (0.138) [1.274] {99329}	-0.297 (0.43) [0.315] {99329}	-1.68 (9.2) [0.031] {99329}	1.066 (3.49) [0.11] {99329}
BW5	0.291 (0.262) [1.334] {87226}	-1.24 (5.52) [0.044] {87226}	-0.54 (0.69) [0.454] {87226}	0.543 (0.424) [2.382] {87226}
BW3	-8.58 (67.231) [0.015] {63589}	1.514 (3.119) [0.276] {63589}	0.741 (0.563) [2.335] {63589}	0.383 (0.31) [1.617] {63589}

Note: Dependent variable is employment status in each regression. Coefficient estimates belong to the effect of high school graduation status. All regressions include controls for regional dummies of NUTS-1 level, age of the individual and survey year. The sample used for regression analysis is limited to individuals who were born in Türkiye. BW is the abbreviation for bandwidth. BW7 refers to maximum symmetric bandwidth of 7 years around 1998 cutoff. BW5 and BW3 refer to 5 and 3 years before and after 1998 cutoff, respectively. Standard errors are birth year-clustered and given in (). Weak IV Test statistics from each regression are presented in []. Number observations are given in {}. *** denotes significance at 1% level, ** denotes significance at 5% level, * denotes significance at 10% level.

Table 4.23 presents results related to the effect of 2012 reform on high school completion status. Accordingly, there is significant positive influence of the reform only for males who were born 5 years before and after 1998 cut-off under quartic functional form specification: those who are subject to new regulation have 3.41 pp. higher probability of graduating high school than those who are subject to previous regulation. For the rest of the bandwidths as well as females there exists no such significant evidence. In line with results from first stage regression of high school completion status on 2012 reform exposure status, the second stage regression of employment status on predicted probabilities of high school graduation status in Table 4.22 produces weak evidence in favor of positive return to high school diploma for males who were born 3 years around 1998: those who graduated high school have 96.2 pp. higher probability of being employed compared to those who have below high school degree. The results in Tables 4.22 and 4.23 imply that there exist no significant evidence in favor of the link between high school graduation and employment probability due to 2012 compulsory schooling law exposure.

Table 4.23. The Policy Effect on High school Completion

Polynomial Degree	First	Second	Third	Fourth
		Male		
BW7	0.0265 (0.055) [2495***]	-0.035 (0.045) [2682***]	-8.5×10^{-5} (0.06) [2532***]	0.0241 (0.042) [2413***]
BW5	0.039 (0.037) [2504***]	-0.0055 (0.039) [2422***]	-0.0203 (0.05) [2281***]	0.0341** (0.0172) [2193***]
BW3	0.0033 (0.015) [2219***]	0.0134 (0.014) [2082***]	0.025* (0.056) [1960***]	0.0294 (0.021) [1851***]
		Female		
BW7	0.076 (0.067) [2134***]	-0.031 (0.055) [2495***]	-0.013 (0.072) [2350***]	0.0179 (0.0548) [2241***]
BW5	0.061 (0.052) [2278***]	-0.011 (0.052) [2258***]	-0.042 (0.062) [2130***]	0.033 (0.0214) [2065***]
BW3	-0.002 (0.021) [2204***]	0.011 (0.021) [2069***]	0.0331 (0.022) [1948***]	0.041 (0.032) [1840***]

Note: Coefficient estimates belong to the regression of high school completion status on exposure to 2012 compulsory schooling law. The status of non-exposure to 2012 reform (where the value of CSL is equal to 0) is the reference category in each regression. All regressions include controls for regional dummies of NUTS-1 level, age of the individual and survey year. The sample used for regression analysis is limited to individuals who were born in Türkiye. BW is the abbreviation for bandwidth. BW7 refers to maximum symmetric bandwidth of 7 years around 1998 cutoff. BW5 and BW3 refer to 5 and 3 years before and after 1998 cutoff, respectively. Standard errors are birth year-clustered and are in (). First Stage F statistics are presented in []. *** denotes significance at 1% level, ** denotes significance at 5% level, * denotes significance at 10% level.

According to Table 4.24 which presents the results of 2SLS regression of employment status on university completion status, the sign of effect of the latter is different across genders: For the male sample and those at bandwidth 3, university graduates tend to have a 41 pp. lower probability of being employed compared to those who are below university graduate level. This effect is under the quartic functional specification and it is sensitive to both functional form and bandwidth selection. Rest of estimates imply that there exists no significant evidence in favor of the effect of university completion on employment probability due to 2012 reform. Based on Weak Identification Test statistics we reject the null hypothesis that instrumental variable is weak for each estimation in male sample. On the other hand, for the female sample and those at bandwidth 3, university graduates tend to be employed with 82.6 pp. higher probability than those who are below university graduates based on quartic functional specification. Under linear functional specification, females who were born 7 years around 1998 university graduates tend to have 57 pp. higher probability of being employed compared to those who are below university graduate level. According to Weak Identification Test statistics we reject the null hypothesis that instrumental variable is weak for the bandwidth 3 under quartic functional specification, for the bandwidth 5 under linear and quadratic specification, and bandwidth 7 under linear functional specification.

Table 4.24. The 2SLS Results of Employment Status and University Completion

Polynomial Degree	First	Second	Third	Fourth
		Male		
BW7	0.395	0.436	0.28	-0.0781
	(0.408)	(0.784)	(0.472)	(0.592)
	[104.1***]	[76.913***]	[70.62***]	[57.86***]
	{49814}	{49814}	{49814}	{49814}
BW5	0.214	0.56	-0.233	0.2
	(0.544)	(0.65)	(0.421)	(0.459)
	[59.28***]	[71.24***]	[82.2***]	[55.174***]
	{39016}	{39016}	{39016}	{39016}
BW3	0.174	0.223	0.069	-0.41***
	(1.003)	(0.437)	(0.58)	(0.033)
	[87.67***]	[99.33***]	[31.91***]	[220.1***]
	{25529}	{25529}	{25529}	{25529}
		Female		
BW7	0.569***	0.741***	0.774***	3.42
	(0.0664)	(0.21)	(0.225)	(38.9)
	[10.71***]	[1.774]	[2.647]	[0.006]
	{41488}	{41488}	{41488}	{41488}
BW5	0.593***	0.684**	0.535	-6.62
	(0.052)	(0.225)	(0.46)	(115.5)
	[4.141*]	[1.689]	[0.272]	[0.004]
	{33261}	{33261}	{33261}	{33261}
BW3	0.934	0.895*	5.341	0.827***
	(0.875)	(0.46)	(56.2)	(0.083)
	[0.21]	[0.715]	[0.007]	[6.102**]
	{22402}	{22402}	{22402}	{22402}

Note: Dependent variable is employment status in each regression. Coefficient estimates belong to the regression of university graduation status on exposure to 2012 compulsory schooling law. All regressions include controls for regional dummies of NUTS-1 level, age of the individual and survey year. The sample used for regression analysis is limited to individuals who were born in Türkiye. BW is the abbreviation for bandwidth. BW7 refers to maximum symmetric bandwidth of 7 years around 1998 cutoff. BW5 and BW3 refer to 5 and 3 years before and after 1998 cutoff, respectively. Standard errors are birth year-clustered and given in (). Weak IV Test statistics from each regression are presented in []. Number observations are given in {}. *** denotes significance at 1% level, ** denotes significance at 5% level, * denotes significance at 10% level.

Table 4.25 presents results related to the effect of new policy on university completion status and the results confirm previously reached results for Sample A as in Tables 4.13 and 4.19. For the male sample, across all bandwidths and under all functional forms, there is strong and significant negative evidence of the impact of the 2012 reform. The magnitude of such an effect ranges between 2.8 pp. and 4.8 pp: For instance; males whose birth year is in 3 years around 1998 and mandated by the law are expected to complete university with 3.3 pp. less probability under 4th order polynomial in centered birth year. However, the evidence related to the impact of the reform on university degree attainment of females is not statistically significant except for two cases that those females who were born 7 years around 1998 and under linear functional form specification and those females who were born 3 years around 1998 and under quartic functional form specification: females whose birth year is in 7 years around 1998 and mandated by the law are expected to complete university with 8.9 pp. less probability under 1st order polynomial in centered birth year. The same effect is equal to 2.3 pp. less probability for females who were born 3 years around 1998 under quartic functional form specification. Finally, greater than 10- first stage F statistics that are provided in the third row of each cell of Table 4.25 together with weak IV test results in Male panel of Table 4.24 , we can safely exclude the possibility of a weak IV problem in the results related to male sample. Weak IV test statistics in the female panel of Table 4.24 indicate that exposure to 2012 compulsory schooling law may not be a good instrument for university degree attainment in the female sample except the cases with bandwidth 7 under linear functional form and bandwidth 3 under quartic functional form.

Table 4.25. The Policy Effect on University Completion

Polynomial Degree	**First**	**Second**	**Third**	**Fourth**
		Male		
BW7	-0.047*** (0.0047) [413.2***]	-0.036*** (0.0041) [387.5***]	-0.0361*** (0.0043) [364.7***]	-0.032*** (0.0042) [344.5***]
BW5	-0.042 (0.0054) [304.4***]	-0.035*** (0.0041) [285.5***]	-0.0312*** (0.00345) [268.7***]	-0.0276*** (0.0037) [253.8***]
BW3	-0.031*** (0.0033) [194***]	-0.031*** (0.0031) [181.8***]	-0.0284*** (0.00503) [171.1***]	-0.033*** (0.0022) [161.7***]

Table 4.25.continued

Polynomial Degree	First	Second	Third	Fourth
		Female		
BW7	-0.088**	-0.029	-0.0319	0.0016
	(0.027)	(0.022)	(0.019)	(0.021)
	[473.7***]	[449.4***]	[423.1***]	[400.6***]
BW5	-0.063**	-0.024	-0.012	0.0013
	(0.031)	(0.019)	(0.022)	(0.019)
	[403.2***]	[382.1***]	[359.8***]	[340***]
BW3	-0.015	-0.016	-0.002	-0.0225**
	(0.032)	(0.019)	(0.024)	(0.009)
	[281.9***]	[265.1***]	[249.6***]	[236.5***]

Note: Coefficient estimates belong to the regression of number of years of schooling (SCH) on exposure to 2012 compulsory schooling law. The status of non-exposure to 2012 reform (where the value of CSL is equal to 0) is the reference category in each regression. All regressions include controls for regional dummies of NUTS-1 level, age of the individual and survey year. The sample used for regression analysis is limited to individuals who were born in Türkiye. BW is the abbreviation for bandwidth. BW7 refers to maximum symmetric bandwidth of 7 years around 1998 cutoff. BW5 and BW3 refer to 5 and 3 years before and after 1998 cutoff, respectively. Standard errors are birth year-clustered and are in (). First Stage F statistics are presented in [].*** denotes significance at 1% level, ** denotes significance at 5% level, * denotes significance at 10% level.

Tables 4.26, 4.27, and 4.28 replicate the same procedure used between Tables 4.20 and 4.25, but with labor force participation status as the outcome variable instead of employment/unemployment status. Because regressions of labor force participation status as the outcome variable are run on the same sample as in regressions of employment status as the outcome variable, first stage regressions which explore the overall effect of 2012 legislation of compulsory schooling extension are the same as Tables 4.21, 4.23 and 4.25.

Table 4.26 presents the results of 2SLS regressions of labor force participation status on predicted number of years of schooling attained. For the male sample, the quartic functional form regression weakly predicts that for those born within 5 years around 1998, an additional year of schooling results in a 16.8% higher probability of participating in the labor force. According to linear specification the same estimate is equal to 24.4% higher probability of participating in the labor force for those who were born within 3 years around 1998. Corresponding Weak IV Test statistics imply the rejection of null hypothesis that instrumental variable is weak. For females, linear functional form regression predicts that only those who were born 5 years around 1998, an extra schooling year results in 13.7% higher probability of participating labor force. Similarly, linear specification predicts that for females who were born within 3 years around 1998 an additional year of schooling results in a 22.5% higher probability of participating in the labor force. Corresponding Weak IV Test statistics imply the rejection of null hypothesis that instrumental variable is weak.

Table 4.26. The 2SLS Results of Labor Force Participation and Years of Schooling

Polynomial Degree	First	Second	Third	Fourth
		Male		
BW7	0.92	-0.197	0.21	0.132*
	(4.74)	(0.198)	(0.227)	(0.074)
	[0.036]	[1.265]	[0.811]	[4.147*]
	{113057}	{113057}	{113057}	{113057}
BW5	0.192	1.041	0.257	0.168*
	(0.11)	(3.003)	(0.188)	(0.082)
	[2.37]	[0.112]	[1.601]	[6.17**]
	{98828}	{98828}	{98828}	{98828}
BW3	0.244**	0.327	0.318*	0.719
	(0.097)	(0.212)	(0.15)	(0.713)
	[12.29**]	[4.412*]	[4.864*]	[0.935]
	{71696}	{71696}	{71696}	{71696}
		Female		
BW7	0.135	-0.116	0.245	0.1321
	(0.091)	(0.143)	(0.352)	(0.085)
	[0.815]	[0.777]	[0.546]	[2.456]
	{99329}	{99329}	{99329}	{99329}
BW5	0.137**	2.165	0.322	0.158*
	(0.052)	(25.7)	(0.386)	(0.074)
	[2.382]	[0.007]	[0.706]	[4.274*]
	{87226}	{87226}	{87226}	{87226}
BW3	0.225***	0.382	0.506	0.42
	(0.058)	(0.358)	(0.41)	(0.53)
	[6.573**]	[1.269]	[1.336]	[0.511]
	{63589}	{63589}	{63589}	{63589}

Note: Dependent variable is labor force participation status in each regression. Coefficient estimates belong to the effect of number of years of schooling variable. All regressions include controls for regional dummies of NUTS-1 level, age of the individual and survey year. The sample used for regression analysis is limited to individuals who were born in Türkiye. BW is the abbreviation for bandwidth. BW7 refers to maximum symmetric bandwidth of 7 years around 1998 cutoff. BW5 and BW3 refer to 5 and 3 years before and after 1998 cutoff, respectively. Standard errors are birth year-clustered and given in (). Weak IV Test statistics from each regression are presented in []. Number observations are given in {}. *** denotes significance at 1% level, ** denotes significance at 5% level, * denotes significance at 10% level.

Table 4.27 presents the results of 2SLS regressions of labor force participation status on predicted probabilities of high school graduation status. There exists no evidence in favor of the effect of high school graduation status on labor force participation status of males. According to corresponding Weak Identification Test statistic at bandwidth 5 we reject the null hypothesis that instrumental variable is weak at 10% level.

Table 4.27. The 2SLS Results of Labor Force Participation and High school Completion

Polynomial Degree	First	Second	Third	Fourth
		Male		
BW7	1.013	-0.69	-285.8	0.985
	(1.96)	(7.25)	(2×10^5)	(1.65)
	[0.236]	[0.61]	[0]	[0.332]
	{113057}	{113057}	{113057}	{113057}
BW5	0.611	-3.92	-1.413	0.867
	(0.555)	(28.36)	(3.67)	(0.508)
	[1.09]	[0.02]	[0.162]	[3.961*]
	{98828}	{98828}	{98828}	{98828}
BW3	9.049	2.1	1.25*	1.54
	(39.56)	(2.36)	(0.56)	(1.061)
	[0.051]	[0.922]	[3.36]	[1.952]
	{71696}	{71696}	{71696}	{71696}
		Female		
BW7	0.33	-0.41	-2.23	1.397
	(0.203)	(0.72)	(1.25)	(4.3)
	[1.274]	[0.315]	[0.031]	[0.106]
	{99329}	{99329}	{99329}	{99329}
BW5	0.474	-1.53	-0.736	0.911
	(0.37)	(7.18)	(1.07)	(0.618)
	[1.334]	[0.044]	[0.454]	[2.382]
	{87226}	{87226}	{87226}	{87226}
BW3	-12.36	2.27	1.06	0.669
	(97.55)	(4.47)	(0.716)	(0.472)
	[0.015]	[0.276]	[2.335]	[1.617]
	{63589}	{63589}	{63589}	{63589}

Note: Dependent variable is labor force participation status in each regression. Coefficient estimates belong to the effect of high school completion. All regressions include controls for regional dummies of NUTS-1 level, age of the individual and survey year. The sample used for regression analysis is limited to individuals who were born in Türkiye. BW is the abbreviation for bandwidth. BW7 refers to maximum symmetric bandwidth of 7 years around 1998 cutoff. BW5 and BW3 refer to 5 and 3 years before and after 1998 cutoff, respectively. Standard errors are birth year-clustered and given in (). Weak IV Test statistics from each regression are presented in []. Number observations are given in {}. *** denotes significance at 1% level, ** denotes significance at 5% level, * denotes significance at 10% level.

Table 4.28 presents the results of 2SLS regressions of labor force participation status on predicted probabilities of university graduation status. There exists weak evidence in favor of the effect of university graduation status on labor force participation status for the following cases for males and the sign of the coefficient is mixed: quadratic specification predicts that those at bandwidth 3 around 1998; university graduates tend to be in the labor force with 56.4 pp. lower probability, linear specification predicts that those at bandwidth 7 around 1998 university graduates tend to be in the labor force with 103 pp. higher probability compared to below university graduates. Corresponding Weak IV Test statistics imply the rejection of null hypothesis that instrumental variable is weak. For females, the effect is positive: quartic specification predicts that those at bandwidth 3 around 1998, university graduates tend to be in the labor force with 73.3 pp. higher probability compared to below university graduates and linear specification predicts that those at bandwidth 7 around 1998 university graduates tend to be in the labor force with 85 pp. higher probability compared to below university graduates. Corresponding Weak IV Test statistics imply the rejection of null hypothesis that instrumental variable is weak.

Table 4.28. The 2SLS Results of Labor Force Participation and University Completion

Polynomial Degree	First	Second	Third	Fourth
		Male		
BW7	1.028**	0.586	0.454	0.0459
	(0.397)	(0.643)	(0.418)	(0.452)
	[104.12***]	[76.91***]	[70.624***]	[57.86***]
	{49814}	{49814}	{49814}	{49814}
BW5	0.723	0.691	-0.035	0.11
	(0.474)	(0.551)	(0.328)	(0.371)
	[59.283***]	[71.24***]	[82.181***]	[55.17***]
	{39016}	{39016}	{39016}	{39016}
BW3	0.441	0.464	-0.17	-0.564***
	(0.674)	(0.455)	(0.449)	(0.045)
	[87.67***]	[99.33***]	[31.91***]	[220.14***]
	{25529}	{25529}	{25529}	{25529}
		Female		
BW7	0.845***	0.924***	1.0006***	3.39
	(0.062)	(0.193)	(0.271)	(37.42)
	[10.71***]	[1.774]	[2.647]	[0.006]
	{41488}	{41488}	{41488}	{41488}
BW5	0.892***	0.863***	0.78*	-3.53
	(0.072)	(0.21)	(0.361)	(66.8)
	[4.141*]	[1.689]	[0.272]	[0.004]
	{33261}	{33261}	{33261}	{33261}
BW3	1.026	1.02*	2.902	0.733***
	(0.583)	(0.47)	(26.84)	(0.088)
	[0.21]	[0.715]	[0.007]	[6.102**]
	{22402}	{22402}	{22402}	{22402}

Note: Dependent variable is labor force participation status in each regression. Coefficient estimates belong to the effect of university completion. All regressions include controls for regional dummies of NUTS-1 level, age of the individual and survey year. The sample used for regression analysis is limited to individuals who were born in Türkiye. BW is the abbreviation for bandwidth. BW7 refers to maximum symmetric bandwidth of 7 years around 1998 cutoff. BW5 and BW3 refer to 5 and 3 years before and after 1998 cutoff, respectively. Standard errors are birth year-clustered and given in (). Weak IV Test statistics from each regression are presented in []. Number observations are given in {}. *** denotes significance at 1% level, ** denotes significance at 5% level, * denotes significance at 10% level.

4.6. Discussion

The empirical evidence from current study points to several key implications regarding the 2012 compulsory schooling reform in Türkiye. Firstly, the reform significantly increased the number of schooling years attained, particularly for the sample consisting of employed individuals. However, the effect is only weakly significant for the broader sample, which includes unemployed and out-of-labor-force individuals, depending on the bandwidth around the birth year cutoff. Moreover, the gains in the number of schooling years are more substantial for females than males. For example, females gained between 0.29 and 0.62 years, compared to 0.18 and 0.41 years for males, in the sample of employed individuals. In contrast, an increase of 0.15 to 0.19 years in schooling for females and 0.09 to 0.18 years for males is reported in the broader sample. The positive effect of the 2012 reform on schooling years aligns with the findings of Aydemir and Kırdar (2017), which reports increases in number of schooling years by more than half a year for both men and women as a result of 1997 reform and the results from Torun (2018), which documents an increase of 0.6 years for females and 0.4 more years for males as a result of the same reform.

In addition to the overall increase in schooling years, the impact of the reform on high school completion status varies between the samples and genders. For the full sample, which includes employed, unemployed, and out-of-labor-force individuals, the reform's impact on high school completion is insignificant for both genders across all functional specifications and bandwidths. Conversely, for the sample of employed individuals only, the reform significantly increased the probability of high school completion for both genders, yet magnitude and significance of the effect are sensitive to functional form specification in the male sample. Females showed a substantial increase in high school completion probability (around 13 pp. – 18 pp.), while males showed a lower and less significant increase (around 4 pp. – 5.6 pp.). The favorable impact of 2012 reform on high school completion is in line with empirical evidence from previously conducted studies for Turkish compulsory schooling legislations in 1997 and 2012. For example, the study by Erten and Keskin (2019) finds increases in high school attendance by 2.9 pp. for females and 5 pp. for males as a result of 2012 reform. The study by Yıldız (2022), which reports increase in high school completion by 14.7 pp. for females and 0.6 pp. for males as a result of the same reform. The study by Torun (2018), which records 4 pp. increase in high school completion rate among females and 3 pp. increase in high school completion rate among males as a result of 1997 reform and the study by Mocan (2014), which finds an increase in the probability of male middle school completion by 13.1 pp. and a larger impact of 17 pp. for females as a result of the same reform.

Along with the observed improvements in years of schooling and high school completion, the reform also demonstrated a positive effect on university degree attainment for both genders in the sample of employed individuals. For example; males and females who are exposed to the new policy are expected to have 16.5 pp. to 23 pp. and 36 pp. to 49 pp. higher probability of having at least university diploma, respectively. Despite these positive effects observed in narrower sample consisting of employed individuals, only; the effect of the reform on university degree attainment in the broader sample consisting of employed, unemployed and out-of-labor force individuals; is mixed in the way that there exist negative strong significant influence of the reform on university completion of males. The same conclusion also applies to the female sample.

Moving beyond educational attainment, the reform's impact on labor market outcomes varies by gender and educational attainment. Specifically, an additional year of education due to the reform increased monthly earnings by between 10.7% - 22% for females, whereas no significant evidence is found in favor of the effect of one year increase in schooling on monthly income of males. Similarly, an additional year of education increased hourly wages by between 10% - 20% for females. For males, there exists no significant evidence in favor of effect of years of schooling attained on monthly income. These estimates, although tend to change depending on functional form specification and bandwidth selection, are quite close to that estimated for China by the study of Fang et al. (2012).

High school graduation due to the reform led to a significant increase in monthly earnings of females (about between 35% - 86% in other words 8.75% - 21.5% per year of schooling) and hourly wages of them (about between 34% - 75% in other words 8.5% - 18.75% per year of schooling). For the male sample; the effect of having a high school diploma on monthly income is found to be insignificant, yet its effect on hourly wage is significant and equal to 132% (33% per year) increase compared to those males who are below high school graduates, and this effect is not robust to either functional form specification or bandwidth selection. However, empirical evidence related to the effect of university graduation on monthly earnings or hourly wages for either gender is not as strong as previous findings. For males; there exist some significant evidence on return on university diploma such that 22.1% increase in monthly income and an increase in hourly wage between 45% - 53%, yet such estimates aren't robust to either bandwidth of functional form specification. For females; on the other hand; being university graduate as a result of being exposed to the new regulation, has a strong positive effect of magnitude between 13% - 39% (3.25% - 9.75% per year of schooling) increase in monthly income. The return on having a university diploma is significantly positive on hourly wage of females, as well, yet the effect is not as robust as in the case of monthly income.

Furthermore, the extension of compulsory education from 8 to 12 years did not have a concrete impact on employment and labor force participation status, except for university completion, which increased the probability of employment and labor force participation for females. Overall, the study highlights the positive short-term effects of the 2012 compulsory schooling reform on educational attainment, particularly for females, but finds limited impacts on higher education and mixed results for labor market outcomes. These findings suggest important policy implications for improving educational attainment and reducing gender disparities in developing countries.

4.7. Conclusion

Using a Regression Discontinuity Design, this study examines the impact of the compulsory schooling reform enacted in Türkiye in 2012. Specifically, by utilizing Household Labor Force Surveys from 2013 to 2022 conducted by the Turkish Statistical Institute, this research investigates the effects of the exogenous increase in compulsory schooling duration from 8 to 12 years. The study analyzes various outcomes, including educational ones such as the number of schooling years attained, high school graduation status, and university graduation status, as well as labor market outcomes such as monthly income, hourly wage, employment status, and labor force participation status, within a Fuzzy RDD framework which designate treatment status based on the year of birth, assigning individuals born after January 1998 to the treated group.

The empirical evidence from the present study regarding the impact of increasing mandatory schooling from 8 to 12 years indicates a significant increase in the number of schooling years attained for the sample consisting of employed individuals. For a broader sample which includes unemployed as well as out of labor force individuals in addition to employed ones, the evidence is weakly significant and it depends on the bandwidth around 1998 cut-off. The gains in number of years of schooling attained due to exogenous compulsory schooling law in 2012 are higher for females than males. The first stage regression of number of years of schooling on exposure status to 2012 reform in the broader sample produces lower estimates in both magnitude and significance and they are sensitive to functional form specification and bandwidths.

In light of the 2012 compulsory schooling reform that mandated 12 years of education, this study also aims to evaluate whether the reform's intended effects have been realized to date. To this end, a binary variable of high school completion status is generated out of replies to educational attainment questions in the survey and this variable is employed in first stage regressions as the scholastic variable instead of years of schooling. Empirical evidence related to the effect of expanding compulsory schooling to 12 years on high school completion status differs between the two main samples of the present study as well as between the genders. For example, impact of the 2012 reform on the probability of high school completion is found to be insignificant for the sample, which includes employed, unemployed, and out-of-labor-force individuals. On the other hand, for the sample, which includes employed individuals only, impact of the 2012 reform on the probability of high school completion is found to be significantly positive for both genders except for the male sample that estimates are significant under higher order polynomial specifications. For females, the 2012 reform significantly increased the probability of high school completion by about 13 percentage points (pp.) - 18 percentage points (pp.). For males, the increase in high school completion probability is lower compared to that of females and weakly significant only: those males who are subject to the new policy are expected to graduate high school with 4.2 pp. – 5.6 pp. more likely. Finally, the point estimates of increase in probability of completing high school are quite larger for females than males in the sample of employed individuals. Such a finding does not hold for those in the sample which includes unemployed and out-of-labor-force individuals in addition to employed individuals.

This study not only attempts to analyze the intended effects of the 2012 compulsory schooling reform but also investigates its spillover effects by examining university completion status. This binary variable, derived from responses to educational attainment questions in the survey, is employed in the first stage regressions as the scholastic variable, similar to the high school completion status variable. The reform not only led to improvements in years of schooling and high school completion but also significantly increased the likelihood of obtaining a university degree for both genders among employed individuals. Specifically, males and females exposed to the new policy have an increased probability of at least a university diploma by 16.5 to 23 percentage points and 36 to 49 percentage points, respectively. Although positive effects were noted in the narrower sample of employed individuals, the impact of the reform on university degree attainment in the broader sample, which includes employed, unemployed, and out-of-labor-force individuals, is more complex. Specifically, the reform has a strongly significant negative effect on university completion rates for males. A similar pattern is observed in the female sample as well.

In order to assess early career effects of recent compulsory schooling reform in 2012 in Türkiye, second stage regressions of a number of labor market outcomes are conducted. According to 2SLS regression of logarithm of monthly income on number of years of schooling attained, an additional year of education due to 2012 compulsory schooling reform doesn’t increase monthly earnings among males. The estimated effect among females is between 10.7% - 22%. An additional year of education due to 2012 compulsory schooling reform rises hourly wages by about between 10% - 20% among females. The estimated effect among males who were born 5 and 3 years around 1998 is between 12% - 16%, yet these estimates are sensitive to functional form specification and bandwidth selection.

The reform-driven increase in high school graduation significantly boosted women's monthly earnings and hourly wages. For men, while high school graduation had no significant effect on monthly income, it did result in a significant increase in hourly wages compared to those without a diploma. However, this effect is sensitive to the choice of functional form and bandwidth. Therefore, females might have benefited the reform more in terms of being induced to graduate high school and have higher return on high school diploma compared to males. Alike number of years of education and high school graduation status, university graduation status is found to be statistically significant in determining monthly earnings and hourly wages particularly for females. Besides, the extension of compulsory education from 8 to 12 years is found to have no concrete impact on employment and labor force participation status. For example being high school graduate due to the reform isn’t significantly related to employment and labor force participation of both genders. Being a university graduate produces mixed evidence for males and females: While those females who are university graduates are more likely to be employed, males are less likely to be employed. The reform's increase in years of schooling has a significantly positive effect on females' likelihood of being employed, although this effect is sensitive to the choice of functional form and bandwidth. For males, an additional year of schooling does not significantly affect their employment probability. Regarding labor force participation, an additional year of schooling has a positive impact, but this effect is also not robust to changes in bandwidth and functional form specifications.

One of the significant findings of the present study is that the 2012 compulsory schooling reform successfully increased individuals' educational attainment, both in terms of years of education and high school diploma acquisition together with that females are affected more favorably. Consequently, the increase in high school attainment among lagging groups carries important implications for policymakers in developing countries. Compulsory schooling policies when combined with monetary and non-monetary schooling costs-reducing provisions by policymakers, can effectively prevent suboptimal schooling decisions and help reduce gender disparities in educational attainment. Furthermore, with the detailed quantitative measures policymakers can identify aspects of the reform that have succeeded and areas that require improvement. This can lead to more informed and targeted modifications to the education system. While the study advances our understanding of educational outcomes and returns to education as a result of recent compulsory schooling expansion in Türkiye, it is limited by the sample that it employs. Due to limitations in data availability, this study is restricted to estimating the returns to schooling for wage / salary earners. It does not, for instance, extend to self-employed individuals, whose returns might be significantly influenced by a broader range of factors including human capital acquisition through education, job experience, personal skills, and entrepreneurial activities. Finally, the conclusions drawn by the present study are only valid for the short-term period following the implementation of the reform and may not be generalizable to the long-term impact of the recent compulsory schooling reform in Türkiye. For future studies, investigating other spillover effects of recent compulsory schooling expansion might be interesting.

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5. CONCLUSION

This dissertation has examined the intricate relationship between educational policies, socioeconomic and demographic factors; and their impact on educational and labor market outcomes in Türkiye through three distinct essays. Each essay has provided critical insights into different aspects of the educational system, offering valuable implications for policy-making, particularly in the context of a developing country with a large and young population.

The first essay delves into the academic performance of Turkish secondary school students, analyzing the predictive power of various socioeconomic and demographic attributes. By employing machine learning techniques on data from the PISA 2018 survey, the study identified significant predictors of student success, highlighting that students from general secondary education high schools tend to outperform their peers. While the study demonstrated the effectiveness of machine learning models in predicting academic outcomes, it acknowledged the limitations in generalizing these findings to other contexts. The essay emphasized the need for further research using administrative records to explore the underlying mechanisms affecting educational achievement, particularly within the stratified Turkish education system.

The second essay employs survival analysis to investigate the expected school duration and dropout risks among Turkish children of compulsory school age. The study revealed significant dropout points at critical transitions between educational levels, with factors such as child employment, household composition, parental education, and regional disparities playing crucial roles in determining a child's likelihood of remaining in education. The findings underscored the importance of addressing socioeconomic inequalities and regional disparities to improve school enrollment and reduce dropout rates in Türkiye. The essay advocated for targeted policies aimed at mitigating the adverse effects of low socioeconomic status and child labor on educational continuity.

The third essay focuses on the impact of the 2012 compulsory schooling reform in Türkiye, which extended mandatory education from 8 to 12 years. Using a

Regression Discontinuity Design framework and data from the Turkish Statistical Institute, the study analyzed the effects of this reform on educational attainment and labor market outcomes. The findings indicated that the reform led to significant increases in the number of years of schooling and high school graduation rates, particularly for females. However, the impact on university completion rates and labor market outcomes, such as income and employment status, was more complex, with gender disparities evident in the results. The essay highlighted the importance of combining compulsory schooling policies with measures to reduce the costs of education, thereby preventing suboptimal schooling decisions and reducing gender disparities in educational attainment.

Collectively, the essays underscore the critical role of educational policies in shaping both educational and labor market outcomes in Türkiye. The findings highlight the need for targeted interventions at specific educational stages, particularly during key transitions between educational levels, to support students at risk of dropping out. The significant gender disparities observed in the impact of the 2012 compulsory schooling reform suggest that future policies should be designed with a focus on promoting gender equality in education. From a policy perspective, this dissertation offers several recommendations. First, educational policies should prioritize reducing regional disparities in access to and quality of education, particularly in economically disadvantaged areas. Second, initiatives aimed at improving the socioeconomic conditions of households and reducing child labor are essential to support students' academic achievements and reduce dropout rates. Lastly, the adoption of advanced data analysis techniques, such as those demonstrated in this dissertation, should be disseminated by employing larger scale data such as administrative records for continuous monitoring and improvement of educational policies.

In conclusion, while this thesis advances the academic understanding of the economics of education, its findings also hold practical implications for shaping future educational policies in Türkiye and other developing countries facing similar challenges. Future research should continue to explore these areas, using diverse data sources and methodologies to validate and expand upon the insights generated in this thesis, particularly focusing on the long-term impact of educational reforms and their spillover effects on broader social and economic outcomes.