Estimating Heterogeneous Impacts Using Causal Forest:
Case Study On The Youth Tomorrow Chaeum Deduction in South Korea

By

KIM, Dohui

THESIS

Submitted to

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ABSTRACT

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Dohui Kim

The labor shortage within small and medium-sized enterprises (SMEs) represents a critical concern in South Korea. In response, the government implemented the *Youth Tomorrow Chaeum Deduction* policy to promote the influx of SMEs and support the long-term employment and asset-building of young workers. However, the policy concluded in 2022, and as of 2023, its scope was restricted to the manufacturing and construction industries. To assess the effectiveness of the policy, the present study introduces two analytical approaches: a *difference-in-differences* and *Causal Forest*. Causal Forest estimates the conditional average treatment effect (CATE) to understand the heterogeneity in the effect of *Youth Tomorrow Chaeum Deduction* for different demographic subgroups. This study suggests that predicting heterogeneous treatment effects through CATE can be a suitable method for policy planning to target policy beneficiaries within a limited budget.

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Chapter 1

Introduction

The duration of youth employment in small and medium-sized enterprises (SMEs) is a notable concern in South Korea, primarily due to the disparities observed in the labor market. This discrepancy arises from the contrasting dynamics between the labor demand from SMEs and the available labor supply for SMEs. According to the Korean Statistical Information Service [Korean Statistical Information Service, 2023], the unemployment rate of youth between the ages of 15 and 34 was 5.4% in 2022, which was 2.5%p higher than the total unemployment rate of all ages over 15 (2.9%). Furthermore, SMEs are experiencing a more serious manpower shortage than large enterprises. The average job vacancy rate for businesses with fewer than 300 employees is 1.1%, almost four times higher than 0.3% for businesses with more than 300 employees in 2020 [Park, 2022]. In order to relieve the discrepancy, the Ministry of Employment and Labor first introduced a youth job policy called Youth Tomorrow Chaeum Deduction in 2016. The purpose of this policy is to support the early career formation for youth newly entering the labor market and to help resolve the manpower mismatch through the influx of youth to SMEs [of Employment and Labor, 2023]. Youth employees can decide whether to enroll or not in this policy.

However, as of 2023, the Youth Tomorrow Chaeum Deduction policy applies only to the manufacturing and construction industries [Ministry of Employment and Labor, 2023]. The Ministry of Strategy and Finance's stance on the policy change is that the 2023 budget aims to resolve the labor supply-demand mismatch by focusing support on small businesses in labor shortage industries. By focusing on manufacturing and construction industries that use foreign labor due to labor shortages rather than all SMEs in 2023, and by targeting small (less than 50 employees) firms, which have relatively severe labor shortages among SMEs, the government hopes to minimize budget execution problems such as the possibility of deadweight loss [Ministry of Strategy and Finance, 2023]. Considering the changes in policy coverage, it is timely to undertake a comprehensive evaluation of the policy's effectiveness.

Existing research conducted by Small and Medium Venture Business Corporation shows that the average job tenure for young employees who enrolled in the policy was 53.3 months, which was 27.9 months longer than 25.4 months for those not enrolled [Park, 2022]. While previous studies have primarily focused on analyzing individual-level effects [Lee, 2018, Kim, 2020], this research intends to broaden the scope by examining more recent data at the industry level. The industries covered by the policy are considered the treatment group, whereas the industries not covered serve as the control group. Using this approach, this study aims to provide a comprehensive understanding of the policy impact on youth tenure in SMEs at the industry level.

The paper investigates the following research questions: How significant are the impacts on the tenure period of youth in SMEs from the Youth Tomorrow Chaeum Deduction policy? And does the impact have a heterogeneous effect across groups or characteristics?

To address this question, two methodologies are utilized. The one is the difference-in-differences method which is commonly employed in policy assessment because of its ability to control for potential variations in the performances of the treated and untreated groups before the implementation of a program ([Bronzini and Piselli, 2016]. The other is a causal forest [Athey and Wager, 2019]. Considering the budget constraint problem faced by policymakers, it is advisable to target individuals who are likely to have a positive effect on the policy rather than treating everyone [Jacob, 2021]. Consequently, this approach allows for the identification of subgroups that exhibit a favorable impact from the policy.

In summary, the present research aims to evaluate the impact of the Youth Tomorrow Chaeum Deduction policy on the overall duration of employment among young workers aged between 20 and 39 in small and medium-sized businesses (SMEs). The research employs a difference-in-differences empirical approach using a large-scale survey of repeated cross-sectional data on labor conditions by employment type. Furthermore, a Causal Forest, an ML method, is utilized to estimate the conditional average treatment effects.

The policy evaluation methodologies using causal forests have been widely used in the United States [Davis and Heller, 2017, Gulen et al., 2020, Hoffman and Mast, 2019]. However, there are very few studies on policy evaluation using the Causal Forest in South Korea. To my knowledge, this research is the first academic paper to formally explore the impacts of youth job policy on tenure as outcomes using a machine learning-based method (Causal Forest).

This research will be of interest to researchers in the field of policy impact, particularly within the realm of public policy. Additionally, the findings hold potential value for the Ministry of Employment and Labor of South Korea, as well as other scholars, engaged in the field of public policy. The dataset utilized in this study spans from 2010 to 2021 and stems from the Survey on Labor Conditions by employment type. Data acquisition was facilitated through a formal request made to the Ministry of Employment and Labor, with the intent of utilizing it for research purposes.

The paper is structured as the following: the initial chapter introduces research questions, provides background information on the study, and outlines the study objectives. Chapter 2 offers an overview of the Youth Tomorrow Chaeum Deduction Policy and presents a comprehensive literature review. Following this, Chapter 3 outlines the data and methods employed in this paper. Chapter 4 delivers the findings from the Difference-in-Differences analysis and the Causal Forest methodology. The final section, Chapter 5, concludes the paper by summarizing key findings and discussing their policy implications.

Chapter 2

Related works

Chapter 2 of this paper begins with an overview of the Youth Tomorrow Chaeum Deduction policy and a literature review related to this policy. Subsequently, the chapter provides related works on the empirical method used, specifically focusing on the adaptation of the causal forest approach to public policy.

2.1 The Youth Tomorrow Chaeum Deduction

The Youth Tomorrow Chaeum Deduction policy is a youth employment promotion project aimed at encouraging young people who have been employed full-time at small and medium-sized enterprises to build assets, thereby promoting full-time employment and long-term employment. The following is a description of the eligibility requirements. First, young people between the ages of 15 and 34 who have newly hired full-time jobs in small and medium-sized enterprises (SMEs) are eligible. In conjunction with the period of compulsory military service, men can be up to the age of 39. In addition, those whose monthly salary exceeds 3 million won are restricted from joining. Wage requirements must be maintained for one year from the date of hiring a regular employee (date of conversion), and the subscription will be withdrawn if the total amount of payment for one year from the date of hiring a regular employee (date of conversion) exceeds KRW 36 million.

In terms of companies, these are small and medium-sized enterprises with five or more employees insured by employment insurance and employ young people as full-time workers. Businesses excluded from the application of the policy include entertainment establishments, public institutions, public enterprises, schools, and businesses other than SMEs. Previously, the real estate industry was an industry subject to exclusion, but since the effective date of June 2021, the real estate industry has been deleted from the non-support industries. So, youth employed as permanent in the real estate industry can also sign up for deduction now. This has been implemented since June 2021, and the data set to be used in the paper is data up to June 2021, so the real estate industry was placed as a control group in this paper.

The accumulation structure of the Youth Tomorrow Chaeum Deduction Policy is asset building through the three-party accumulation of youth, companies, and the government. The young person himself will accumulate 125,000 won every month for 2 years, totaling 3 million won. Companies are classified according to the size of the company and the amount and method of accumulation and support and will accumulate 3 million won for 2 years. As for government subsidies, 6 million won for 2 years of employment subsidies will be accumulated for 2 years, 3 million won for young people, 3 million won for companies, and 6 million won for the government. The following amounts are supported (accumulated) by cycle for 24 months (2 years) from the date of application acceptance (the date of establishment of the deduction contract). 800,000 won (800,000 won) for 1 month, 1.2 million won (2 million won) for 6 months, 1.2 million won (3.2 million won) for 12 months, 1.4 million won (1.6 million won) for 18 months, 1.4 million won (6 million won) for 24 months. Therefore, for two years, the youth will accumulate 3 million won, the company 3 million won, and the government 6 million won. Young people employed by SMEs will receive a total of 12 million won when they work for two years as full-time employees. Figure 2.1 shows the trend graph of the numbers of receipts of installment savings, Enterprise, Youth, and Savings account cancellations. Figure 2.2 shows the accumulation structure of the Youth Tomorrow Chaeum Deduction by the size of the company. However, since 2023, due to the reorganization of the Youth Tomorrow Tomorrow Chaeum Deduction, the industry has been limited to small and medium-sized companies in the construction and manufacturing industries with more than 5 people and less than 50 people. In addition, in the past, entrepreneurs had to pay differentially according to the size of the company (the rest was supported by the government), but now it has been reorganized so that the company bears 100% of the burden.

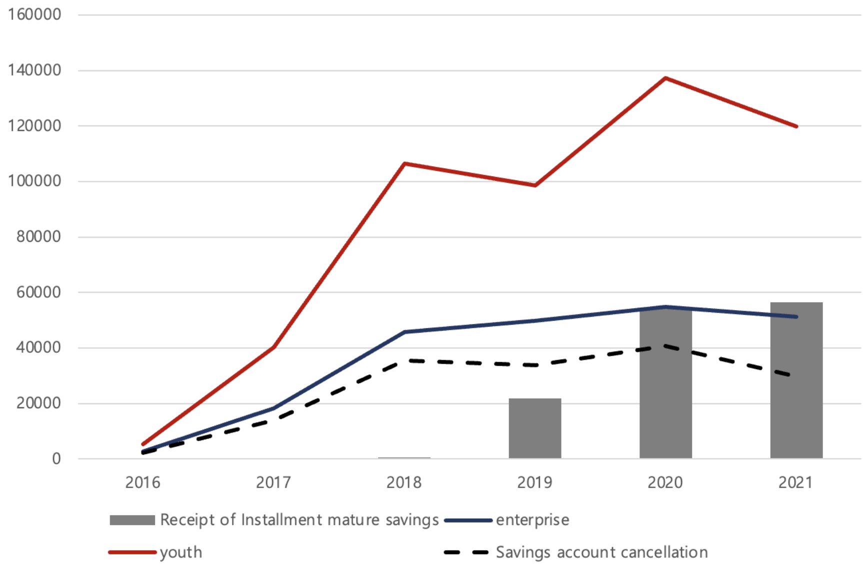

Figure 2.1: Trend of subscription, cancellation, and receipt of the Youth Tomorrow Chaeum Deduction

Note: [Park, 2022] as cited in Ministry of Employment and Labor, 2022. The graph is restructured by the author.

Figure 2.2: The accumulation structure [Ministry of Employment and Labor, 2022]

Note: As of 2023, there has been a change in the accumulation structure [Ministry of Employment and Labor, 2023].

At present, there is a lack of evaluations utilizing Machine Learning methods to assess the heterogeneous effects of the Youth Tomorrow Chaeum Deduction Policy in South Korea. The analysis of the effectiveness of the Youth Tomorrow Chaeum Deduction was conducted mainly through statistical comparison and FGI [Kim, 2020, Lee, 2018]. Existing research conducted by Korea SMEs and Startups Agency shows that the average job tenure for young employees who enrolled in the policy was 53.3 months, which was 27.9 months longer than 25.4 months for those not enrolled [Park, 2022]. Kim (2020) shows, through statistics, the ratio of those who have expired and those who are in the middle of the Youth Tomorrow Chaeum Deduction. Lee (2018) reported the participants' evaluation of the policy through Focus Group Interviews. The strength of the existing research is that it analyzes the effect of the policy from the individual point of view that has benefited more from the policy. However, all existing studies on the Youth Tomorrow Chaeum Deduction policy impact above mentioned have been conducted at the individual level [Kim, 2020, Lee, 2018], and studies have not examined job tenure at the industry level. So, this paper intends to examine more recent data at the larger industry level by dividing industries not covered as the control group and industries covered by the policy as the treatment group. Also, considering that there was a policy change limiting the eligibility for policy application and the applicable industries from early 2023, it is timely and necessary to explore the effectiveness of policies at the industry level.

2.2 Causal Forest in Public Policy

The widespread use of impact evaluation (or IE) methodologies for assessing the potential consequences of policies or programs on outcomes of interest has resulted in a movement in economic research toward an empirical approach. These methodologies, however, rely on fundamental presumptions, like the linearity and homogeneity of treatment effects, that may not hold in actual practice.

To address these limitations, Wager and Athey (2018) suggested a causal forest, which predicts treatment impacts depending on high-dimensional, analyzing the data for each subgroup systematically and nonlinear functions of observations. This method would allow for more flexible estimation of treatment heterogeneity. Also, the causal machine learning method identifies significant heterogeneity in policy effects. This allows researchers to identify a subgroup with heterogeneous policy impacts. The research also can characterize those who profit from it by developing tests for whether predicted heterogeneity works when detecting real heterogeneity and using heterogeneity patterns to assess possible mechanisms.[Davis and Heller, 2020].

The various studies using the causal forest in policy impacts have been recently conducted [Hoffman and Mast, 2019, Khazra, 2019, Davis and Heller, 2020, Gulen et al., 2020, Kreif et al., 2020, Lechner, 2023]. Davis and Heller (2020) analyze heterogeneous treatment effects for a summer jobs program in Chicago. They find that youth who experience the greatest advantages from post-program employment tend to be of a younger age, have higher school attendance rates, belong to the Hispanic ethnicity, are more likely to be female, and have no arrest records. Hoffman and Mast (2019) also adapted the causal forest to identify heterogeneity in the impact of federal expenditure on local crime and identified a more pronounced effect, particularly in counties with below median income levels. Khazra (2019) estimates the elasticity of house prices on consumption as a non-parametric function of time, locations, and household features using a causal forest. The result provides that household size, having a child, and the age of a household head, among all characteristics, generate significant disparities. Areas with volatile housing markets have negligible elasticity. Khazra (2019) concludes that policymakers should consider this geographic and individual heterogeneity in consumption responses to house price changes when formulating policy. Gulen et al. (2020) used RDD, and causal forest together in the context of corporate finance. Unlike the RDD, the unbiased treatment effects could be recovered by Causal Forest even when company manipulates to evade a technical default. Causal forest results show that the companies most negatively impacted by technical defaults are those that are less able to repay their lenders. Kreif et al. (2020) used the causal forest and found notable heterogeneity in the impact of the contributory insurance scheme. Specifically, vulnerable mothers who fall into the lower wealth quintiles, have less education or live in rural areas benefit the most from the scheme in terms of higher utilization of healthcare. The subsidized plan had little discernible heterogeneity, despite the program's focus on underprivileged groups. Lechner (2023) initiated an evaluation research to examine the effectiveness of the Active Labor Market Program (ALMP) in Flanders. ALMPs are programs that primarily aim to improve the re-employment chances of the unemployed. The main focus was to answer the questions 'who should be sent to which program' and 'which programs work for whom'. The paper estimated the group average treatment effect (GATE) for four different proficiency levels in Dutch (the regional language of Flanders).

The results showed that program effectiveness decreases as proficiency in Dutch increases.

The utilization of causal forest analysis in research papers offers a notable benefit by facilitating the identification of key variables that maximize the heterogeneous effects observed between treatment and control groups. These identified characteristics can subsequently serve as valuable criteria for selecting potential beneficiaries of policies. In essence, applying a causal forest model can reveal heterogeneous program impacts, which can provide policy makers with important information for program design. Nevertheless, the investigation of the heterogeneous impact of policies in the Korean context has received limited attention in the literature. The following chapter provides a comprehensive summary of the data and methodologies used in conducting this study.

Chapter 3

Data and Methodology

3.1 Data

The present study utilizes the survey data on Labor Conditions by Employment Type, which has been publicly released by the Ministry of Employment and Labor. The purpose of the survey is to classify workers (including special type workers) in businesses with one or more workers into various employment types to understand their working conditions, including wages working hours, and provides a primary data source for labor policies. The dataset utilized in this study encompasses essential demographic details concerning employees, along with workplace characteristics. Consequently, the availability of such data allows for an examination of the effectiveness of the policy through the division of subjects into treatment and control groups.

The Survey Report on Labor Conditions by Employment Type contains the findings of an annual survey on working days, working hours, wages, etc. at a sample of about 33,000 establishments and has been conducted annually since 2000. The survey is organized into two main scopes. One is (1) business establishments. This is total sample of 33,000 businesses selected by using statistical methods throughout all private industrial sectors with one or more employees except the followings: National and local administrative agencies, Military, police and national/public educational institutes, International organizations and foreign agencies, Household service providers, Agriculture, forestry and fishing businesses owned by individuals. The second is (2) Workers, which is a sample of paid workers, excluding the self-employed, employers, and unpaid family workers, etc. The dataset includes the following variables: industry, business size, employment type, gender, education, age, year of hire, month of hire, tenure, etc. for a sample of about 33,000 businesses per year (Ministry of Employment and Labor, 2022).

The purpose of this study is to examine the impact on employment within small and medium-sized enterprises (SMEs), with a particular focus on the tenure of young employees in SMEs. For the purpose of this research, SMEs are defined as companies employing between 5 and 299 employees. The analysis focuses specifically on full-time positions and targets young adults aged 34 or younger for women, and aged 39 or younger for men, who are eligible to participate in the Youth Tomorrow Chaeum Deduction policy. To ensure the integrity of the analysis, certain observations have been excluded. Specifically, data points with less than one year of employment, but with a monthly salary exceeding KRW 3 million, have been omitted based on the income threshold set by the Youth Tomorrow Chaeum Deduction policy. Until June 2021, the real estate sector was not included in the industries targeted by the policy. Therefore, the treatment group in the dataset consists of all industries except the real estate industry, and the control group solely consists of the real estate industry. It is important to note that the dataset utilized in this study is a representative sample population. Thus, all statistical measures and regression outcomes presented in this paper have been weighted to reflect the population. Table 3.1 compares the summary statistics of the variables used in this study.

Table 3.1: Summary statistics (2010-2021)

		Treated	industry	Control	industry
Variable	Level	Freq.	Pct(%)	Freq.	Pct(%)
Gender	male	1,188,677	66.07	28,100	71.57
	female	610,321	33.93	11,161	28.43
Education level	Middle school graduate or lower	8,856	0.49	81	0.21
	High school graduate	435,808	24.23	8,119	20.68
	Associate Degree	449,032	24.96	8,379	21.34
	Bachelor's degree	838,232	46.59	21,215	54.04
	Master's Degree or over	67,070	3.73	1,467	3.74
Business scale	5 - 29	554,812	30.84	11,926	30.38
	30 - 299	1,244,186	69.16	27,335	69.62
Classification of Occupations	Managers	8,707	0.48	155	0.39
	Professional and related workers	560,461	31.15	7,652	19.49
	Clerks	593,461	32.99	19,029	48.47
	Service workers	92,946	5.17	671	1.71
	Sales workers	115,193	7.99		
		6.4 3,136			
	Skilled agricultural, forestry and fishery workers	7,504	0.42	36	0.09
	Craft and related trades workers	130,654	7.26	2,635	6.71
	Equipment, machine operating and assembling workers	224,525	12.48	4,939	12.58
	Elementary workers	65,547	3.64	1,008	2.57

Table 3.1: Summary statistics (2010-2021) (Continued)

Types of work shifts	No shift work	1,573,994	87.49	35,323	89.97
	2-shift work	119,614	6.65	1,000	2.55
	3-shift work	96,233	5.35	1,801	4.59
	Every other day shift	7,178	0.4	1,125	2.87
	Part-time work	1,979	0.11	12	0.03
Income (1,000 won)	Regular income	2,353.07		2,513.23	
	special income	3,658.15		4,149.41	
	excess income	194.7774		117.8699	
Industry	Agriculture, forestry and fishing	17,278	0.96		
	Mine	5,448	0.3		
	Manufacturing	405,801	22.56		
	Supply of electricity, gas, steam and air conditioning	31,777	1.77		
	Water, sewage and waste treatment, raw material recycling	17,737	0.99		
	Construction	66,851	3.72		
	Wholesale and retail	191,508	10.65		
	Freight and warehousing	129,690	7.21		
	Accommodation and F&B Business	106,942	5.94		
	information and communication	149,362	8.3		
	Finance and insurance	83,850	4.66		
	Professional, scientific and engineering services	107,396	5.97		
	Business facility management, business support and rental services	76,529	4.25		
	Educational services	54,836	3.05		

	Health and social welfare services	190,754	10.6		
	Services related to arts, sports and leisure	59,228	3.29		
	Associations and organizations, repair and other personal services	104,011	5.78		
	Real estate			39,261	100
Labor Union	Join	259,257	14.41	7,468	19.02
	Not join	1,535,472	85.35	31,788	80.97
	Missing	4,269	0.24	5	0.01
National pension	Join	1,732,815	96.32	39,163	99.75
	Not join	11,185	0.62	96	0.24
	Exclusion criteria for registration	54,998	3.06	2	0.01
Working time	Prescribed working days	20.53096		20.95124	
	Working days on holidays	0.251802		0.5620312	
	Prescribed working hours	169.8443		168.2277	
	Working hours on holidays	3.508731	1.274293		
	Overtime working hours	13.60367	6.865592		
N(obs)		1,798,998		39,261	

Note: This table presents summary statistics of each variable. The sample includes paid workers of 33,000 establishments per year between 2010 and 2021. The data comes from the Survey Report on Labor Conditions by Employment Type published by the Ministry of Employment and Labor. The survey was conducted in June of each year. Business scale represents the number of employees in its company. Regular income is on a monthly basis.

3.2 Methodology

This subchapter introduces the two methodologies used to analyze the effectiveness of the Youth Tomorrow Chaeum Deduction.

In the initial section, the study introduces the difference-in-differences(DiD) methodology to ascertain the treatment effects on the subset of treated entities. The DiD design enables the numerical estimation of the average treatment effect (ATE) by comparing treated and untreated observations, thereby providing insights into the effectiveness of the policy implementation.

The next section utilizes causal machine learning techniques to effectively estimate heterogeneous treatment effects (HTE). Using this approach, the study aims to capture heterogeneity in the impact of a policy on different subgroups or individuals by estimating the conditional average treatment effect (CATE).

3.2.1 Difference-in-Differences

The econometric model takes the following equation to examine the causal effect of the Youth Tomorrow Chaeum Deduction policy introduction on the job tenure of new young employees in SMEs:

$$Y_{ijt} = \beta_1 \cdot \mathrm{Treat}_i \cdot \mathrm{Post}_t + \beta_2 \cdot \mathrm{Treat}_i + \beta_3 \cdot \mathrm{Post}_t + X_{ijt} + \gamma_j + \tau_t + \epsilon_{ijt} \quad (1)$$

Y_{ijt} indicates the months of job tenure of observation i in industry j in year t. Treat_i is a dummy variable that takes one if industry j to which individual i belongs was a policy-applied industry. Post_t is a dummy variable denoting the periods after the policy introduction. Post_t takes a value equal to one for the year of policy introduction in 2016 or later. X_{ijt} is a set of characteristics of each observation i in industry j at year t. ϵ_{ijt} is clustered at the industry level. The error term, ϵ_{ijt}, is clustered at the industry level to deal with a serial correlation of the error term. τ_t denotes year-fixed effects, and γ_j indicates industry-fixed effects. The product(interaction) term between Treat_i and Post_t, β_1 is the coefficient of interest is. It estimates the effect of the implementation of the Youth Tomorrow Chaeum Deduction policy on the job tenure period of new youth employees in SMEs. The individual-fixed effects could not be included because the dataset is repeated cross-sectional. The estimated causal effect comes from comparing individuals in the treated industries with individuals in the control industry.

The key identifying assumption is that the average tenure period of industries with policy introduced and those of industries where the policy is implemented and industries without the policy would not exhibit different changes in the absence of the youth job policy. To augment the empirical analysis, a difference-in-differences event study framework relative to a base year is employed:

$$Y_{it} = \sum_t \beta_t \left(\text{Treat}_i \times \text{Year}_t\right) + \beta_2 \text{Treat}_i + \beta_3 \text{Year}_t + X_{ijt} + \gamma_j + \tau_t + \epsilon_{it} \quad (2)$$

Here, Year_t represents an indicator variable corresponding to a particular year t from 2010 to 2021, with 2010 as the excluded category. The coefficients β_t measure the effect of the policy on the average youth tenure relative to the base year 2010, which is the starting point of the dataset. This approach allows for a comparative analysis of the policy's effects over time. Figure 4.1 displays the plot of these coefficients. Table 3.2 shows key variables used in difference-in-differences study.

Table 3.2: Variables for Difference-in-Differences.

Type	Feature name
C1	Category of Industry
C2	Business scale
C3	Employment type
C4	Gender
C5	Education level
C6	Types of work shift
C7	Classification of occupation
C8	Labor union
C9	National pension
C10	Year
X1	Age
X2	Regular income
X3	Special income
Y	Tenure (months), outcome variable
D	Treatment, policy application

Note: Variables from the Labor Conditions by Employment Type survey published by the Ministry of Employment and Labor. Based on policy eligibility criteria, the study utilizes age and employment type variables only for selecting observations, and women aged 34 or younger and men aged 39 or younger, who are permanent employees are selected.
Treated industry: Agriculture, Forestry and Fishing, Mine, Manufacturing, Supply of electricity, gas, Steam and air conditioning, Water, sewage and waste treatment, raw material recycling, Construction, wholesale and retail, freight and warehousing, Accommodation and F&B Business, information and communication, finance and insurance, professional, scientific and engineering services, Business facility management, business support and rental services, educational services, Health and social welfare services, Services related to arts, sports and leisure, Associations and organizations, repair and other personal services. *Control industry:* Real estate

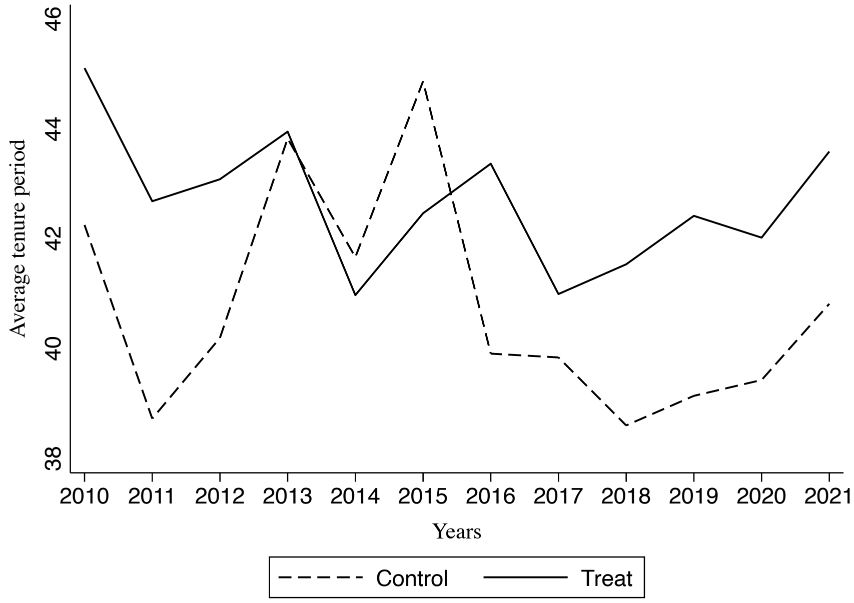

Figure 3.1: Trend of job tenure period over year

Note: This figure displays the average job tenure period of youth employees in SMEs between 2010 and 2021. Treatment industries are those affected by the policy implemented in 2016, while the control industry refers to the industry that was not affected by the policy.

The figure 3.1 shows a similar up-and-down trend before 2016. In addition, before the policy implementation year (2016), the treatment group had a lower average tenure compared to the control group, but after 2016, the treatment group has a higher average tenure trend than the control group.

3.2.2 Causal forest

The study also employs the Causal Forest methodology, a form of causal machine learning, to predict the individualized treatment effect of the policy intervention on employee tenure. The Causal Forest proves beneficial when dealing with high-dimensional data (i.e., data with numerous covariates) and in situations where policymakers lack knowledge regarding specific subgroups to target. By estimating the treatment effect on each individual observation by considering their covariates, the Causal Forest approach facilitates the identification of heterogeneity in treatment effects and the identification of key characteristics that drive different treatment outcomes [Jacob, 2021].

Figure 3.2 [Jacob, 2021] gives the simple causal structure. The first graph illustrates that only the treatment variable directly affects the outcome. In this case, the treatment effect is not influenced by any additional covariates. The second graph, on the other hand, incorporates additional covariates that could potentially affect the treatment effect based on certain features. In the third graph, the covariates not only affect the treatment effect but also affect the probability of receiving the treatment. The researcher has no control over treatment assignment, so this setup is an observational study. The first and second schemes are considered randomized controlled trials (RCTs). In RCTs, treatment assignment is typically randomized, ensuring a balanced distribution of covariates between the control and treatment groups. The randomization allows for an unbiased estimation of the average treatment effect (ATE). The focus is primarily on estimating the overall treatment effect across the entire population. In contrast, the second and third graphs incorporate additional covariates that have the potential to modify the treatment effect based on specific characteristics. In these settings, treatment heterogeneity and estimation of the CATE become possible. The presence of covariates allows for subgroup analysis, where the treatment effect can be estimated separately for different subgroups defined by the covariates. This provides insights into how the treatment effect varies across various groups based on their characteristics. Therefore, while the first two settings are suitable for measuring the overall treatment effect in RCTs, the inclusion of additional covariates in the second and third graphs enables the examination of treatment heterogeneity and estimation of the CATE [Jacob, 2021]. In this research, the treatment group is divided based on whether the industry is covered by the policy, which aligns more closely with the second graph in terms of the causal structure.

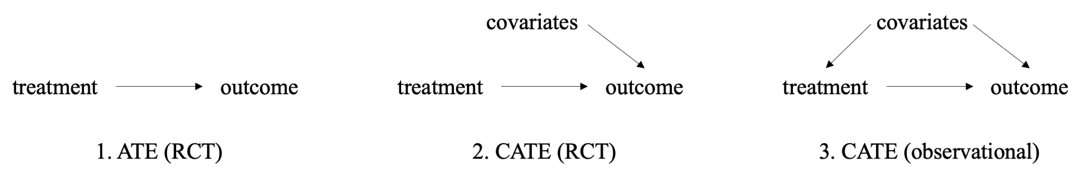

Figure 3.2: Simple causal schema [Jacob, 2021].

This paragraph describes the potential outcomes framework and notations. For each observation, there are two potential outcomes, Y^1 if someone received the treatment and Y^0 if not. $D \in \{0; 1\}$ is the binary treatment indicator and observed covariates are denoted like this $X \in \mathbb{R}$. In order to interpret the estimated parameters as causal, it is necessary to satisfy four key assumptions [Rubin, 1980, Jacob, 2021].

(1) Conditional independence

$$(Y_i^1, Y_i^0) \perp D_i | X_i. \tag{3.1}$$

(2) Stable Unit Treatment Value Assumption (SUTVA) (or counterfactual consistency)

$$Y_i = Y_i^0 + D_i(Y_i^1 - Y_i^0) \tag{3.2}$$

(3) Overlap Assumption

$$\forall x \in supp(X_i), 0 < P(D_i = 1|X_i = x) < 1, P(D_i = 1|X_i = x) \stackrel{\text{def}}{=} e(x) \tag{3.3}$$

(4) Exogeneity of covariates

$$[Y_i^1 - Y_i^0.] \tag{3.4}$$

Assumptions 1 and 4 declare that the allocation of treatment is unrelated to the potential outcomes and that the treatment has no impact on the covariates. Assumption 2 ensures the absence of spillover effects, interference, and hidden variation between treated and untreated observations. Assumption 3, known as the Overlap Assumption, states that there are no subpopulation defined by $X_i = x$ which is entirely confined to either the control or treatment group, hence the probability of treatment must be bounded between 0 and 1. Equation (3.1) is referred to as the propensity score [Jacob, 2021].

The conditional expectation of the outcome for the control or the treatment group is defined as follows

$$\mu_d(x) = E[Y_i \mid X_i = x, D_i = d] \quad \text{with} \quad D \in \{0, 1\} \tag{3.5}$$

The CATE $\tau(x)$, the parameter of interest, is formally defined as:

$$\tau(x) = E[Y_i^1 - Y_i^0 \mid X_i = x] = \mu_1 - \mu_0(x) \tag{3.6}$$

Equation 3.7 illustrates the process by which the estimation of the Conditional Average Treatment Effect (CATE) is derived by subtracting the two conditional mean functions.

$$\begin{aligned}
\tau(x) &= \mu_1(x) - \mu_0(x) \\
&= E[Y_i \mid D_i = 1, X_i = x] - E[Y_i \mid D_i = 0, X_i = x] \\
&= E[Y_i^1 \mid D = 1, X_i = x] - E[Y_i^0 \mid D = 0, X = x] \\
&= E[Y_i^1 \mid X = x] - E[Y_i^0 \mid X = x] \\
&= E[Y_i^1 - Y_i^0 \mid X = x]
\end{aligned} \tag{3.7}$$

This estimator represents whether there is a difference in the effect of the treatment in the population and how large that difference is. Some people and groups can have a positive effect, while others can have a negative effect. The CATE provides the distribution of the effects and enables the identification of subgroups that benefit from policy intervention. If budget constraints exist, rather than treating the entire population, focusing on the groups that exhibit a positive effect of the policy becomes a viable option [Jacob, 2021]. The explanation of the Causal Forest method in this section has been adapted and reorganized based on the paper conducted by Jacob (2021).

Causal Forest is an extend version of random forests (RF) [Breiman, 2001]. While the tree splitting criterion of regression RF focuses on reducing mean squared error, CF aims to maximization of the difference in causal effects. CF adapts a concept of honest trees by dividing the training data into two subsets: one for splitting and the other for estimation. The aforementioned splitting criteria are applied to the partitioned subsets to construct each causal tree. These trees are then adapted to the estimation subset. Similar to the logic of a random forest, CF fits multiple trees and averages the results [Shuryak, 2023].

To estimate the CATE, the study imports Causal Forest DML from the double machine learning module (DML) [Chernozhukov et al., 2017] of EconML. The CausalForestDML refers to a Causal Forest [Athey et al., 2019] combined with double machine learning-based residualization of the treatment and outcome variables [Microsoft, 2023b].

It allows for fitting non-linear models and estimating confidence intervals when dealing with a single-dimensional continuous treatment or binary treatment. It performs well even with high-dimensional features, as long as only those features are relevant [Microsoft, 2023a]. The Causal Forest model adapts LassoCV in scikit-learn as the model_y parameter, LogisticRegressionCV(solver='lbfgs' , max_iter=3000) as the model_t parameter, criterion ="het", discrete_treatment=True, and other parameters are set to EconML's default parameters. A regression method, lasso (Least Absolute Shrinkage and Selection Operator) functions for regularization and variable selection [Tibshirani, 1996]. The criteria is a function that measures the quality of the split. The supported criteria for "het" is the heterogeneity score [Microsoft, 2023b]. In accordance with Knittel and Stolper

(2019), the study select a random 50% sample to train the causal forest and test its performance on the other half. The paper also provides a plot utilizing SHAP (SHapley Additive exPlanations) values. SHAP is an open-source library for interpreting black-box machine learning models using the Shapley value methodology based on the game theoretic approach. SHAP values can be very helpful in understanding the leading factors of effect heterogeneity that a model captured in its training data and shows feature importance [Lundberg and Lee, 2017].

Given that the analysis focuses on identifying heterogeneous effects of outcome values after the policy implementation, only post-policy observations from 2016 onwards are considered. Table 3.1 demonstrates that the two groups have similar mean values for most characteristics. The machine learning analysis aims to identify heterogeneous effects specific to certain features or groups. Hence, variables with multiple categories and significant characteristics are selected. Table 3.3 shows the variables used in Causal Forest.

Table 3.3: Variables for Causal Forest.

Type	Feature name
C1	Category of Industry
C2	Business scale
C3	Employment type
C4	Gender
C5	Education level
C6	Types of work shift
C7	Classification of occupation
X1	Age
X2	Prescribed working days
X3	Working days on holidays
X4	Prescribed working hours
X5	Overtime working hours
X6	Working hours on holidays
X7	Income
X8	Over income
X9	Special income
Y	Tenure (months), post-treatment outcome
D	Treatment, policy application

Note: Variables from the Labor Conditions by Employment Type survey published by the Ministry of Employment and Labor.

Chapter 4

Results

The Youth Tomorrow Chaeum Deduction has been highly praised by SMEs and public officials for its effectiveness in promoting new employment, with participants having a higher probability of staying in the same company than non-participants and a higher probability of remaining in the labor market when changing jobs [Ministry of Employment and Labor, 2021].

This research goes further to present findings on whether the policy have an impact on improving employee tenure across policy-treated industries and spillover effects such as income. To evaluate the impact of the Youth Tomorrow Chaeum Deduction on the tenure of young individuals in SMEs, a difference-in-differences is employed to calculate the average treatment effect (ATE). Subsequently, to uncover heterogeneous effects based on gender, education level, industry, and occupation category, the Causal Forest, a machine learning-based model, is employed. This approach allows us to identify conditional treatment effects (CATE) that may be masked from the ATE estimates. This approach can help policymakers to target policy beneficiaries more effectively given limited budgets.

4.1 Average treatment effect

Here, the subchapter provides empirical findings regarding the impact of the Youth Tomorrow Chaeum Deduction Policy on the tenure and the monthly income of employees in small and medium-sized enterprises (SMEs) analyzed by difference-in-differences. Table 4.1 and Table 4.2 brief the main results of the analysis.

Table 4.1: The effect of policy on the job tenure and income of youth employee in SMEs

Variable	Tenure	Monthly income
TreatxPost	5.516*** (1.082)	-42.83*** (13.72)
Observations	1,838,259	1,838,259
Adj. R-squared	0.220	0.304
Industry FE	Y	Y
Year FE	Y	Y
Additional Controls	Y	Y

Note: This table presents the linear regression analysis result of the youth job policy effect on the job tenure of new young employees in SMEs. Treatment indicates whether the industry was affected by the policy. Post takes a value of one for the year 2016 or any subsequent year. All specifications include year and industry-fixed effects with additional controls. Standard errors are clustered by industry.
Robust standard errors in parentheses (* $p<0.1$, ** $p<0.05$, *** $p<0.01$)

The obtained results, displayed in Table 4.1, stem from a regression analysis based on the equation provided in column (1). The estimate of Treat x Post is statistically significant. The result reveals that the policy has led to an approximate increase of 5.5 months in the tenure period of young employees, controlling for individual characteristics. In contrast, to increase in the average tenure period, The interaction term between the treatment and post value has a negative relationship with the income value. There is a decrease of 42.83 thousand won (Korean) in the monthly income, holding all other independent variables constant in the model.

The fundamental underlying assumption of the Difference-in-Differences strat-

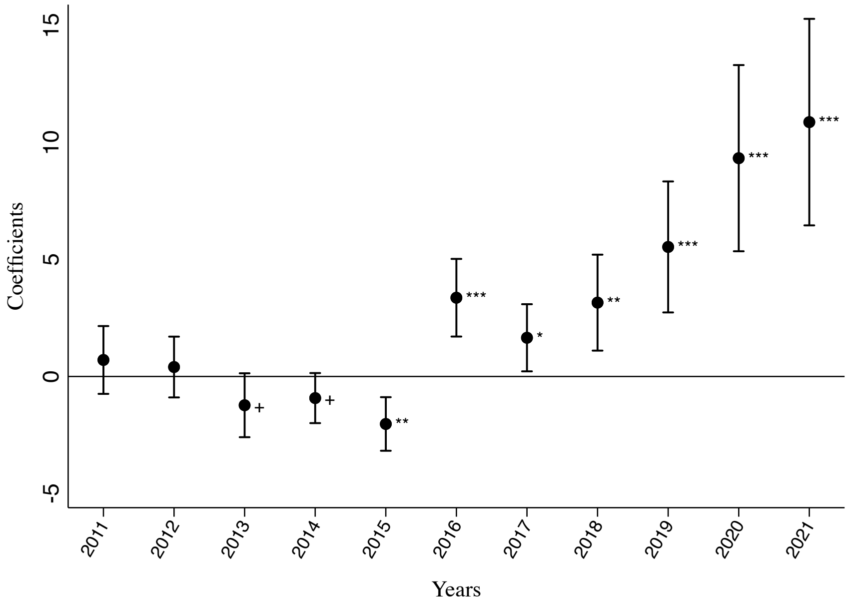

Figure 4.1: Time varying estimates for effects of policy on tenure period

Note: The figure shows regression coefficients and 95% confidence relative to the base year 2010 obtained from linear regression where the dependent variable measures average job tenure of youth employee in SMEs per industry and year, and the variable treat equals 1 for industry which was applied youth tomorrow policy. The control group consists of industry which was not applied the policy. The variable year t represents an indicator variable for each year between 2010 and 2021, and 2010 is the excluded category.
Standard errors are clustered at the level of industry. (* $p<0.1$, ** $p<0.05$, *** $p<0.01$)

egy is that observations who belong to the industries with policy and those without would not develop in distinct ways in the absence of the policy.

Figure 4.1 illustrates the coefficients corresponding to each year relative to the base year of 2010, as derived from equation (2). Notably, the coefficient for the year 2016 demonstrates a statistically significant increase in the tenure period of young employees in SMEs. Interestingly, before 2016, when the policy was initially implemented, the coefficient exhibits significant negative estimates. However, following the year 2016, positive estimates become apparent. This indicates that before the policy implementation, the treatment group experienced a more pronounced decrease in average tenure years compared to the control group. However, this trend reversed after the policy took effect. These findings lend support to the validity of the parallel pre-trend hypothesis.

Table 4.2: The effect of policy on the job tenure and income of employees who worked over 24 months in SMEs

Variable	Tenure	Monthly income
TreatxPost	1.174 (1.449)	-140.0*** (24.81)
Observations	3,217,209,	3,217,209
Adj. R-squared	0.256	0.340
Industry FE	Y	Y
Year FE	Y	Y
Additional Controls	Y	Y

Note: This table presents the linear regression analysis result of the youth job policy effect on the job tenure and the income of employees who worked over 24 months in SMEs. Treatment indicates whether the industry was affected by the policy. Post takes a value of one for the year 2016 or any subsequent year. All specifications include year and industry-fixed effects with additional controls. Standard errors are clustered by industry.
Robust standard errors in parentheses (* p<0.1, ** p<0.05, *** p<0.01)

According to the previous results, the tenure of young people working in the targeted industries increases compared to those who do not. Since the policy targets only new hires, the study also investigates whether there is a spillover effect of the Youth Tomorrow Chaeum Deduction Policy on the job tenure of existing employees. The findings regarding these spillover effects can be found in Table 4.2. The results of a regression analysis are based on the equation provided in column (1). The analysis focuses on a sample of workers who have a tenure of over 24 months. The findings indicate that the introduction of the policy leads to an increase of approximately 1.2 months in the tenure period of these workers. However, the estimated coefficient for this effect is not statistically significant. The implementation of the policy does not result in a significant change in job tenure for workers who have worked for more than 24 months. While the policy has a positive impact on the tenure of young individuals in small and medium-sized enterprises (SMEs), there is no discernible effect on the length of service for existing employees. Furthermore, the interaction term between the treatment and post value exhibits a negative relationship with the income variable. Specifically, holding all other independent variables constant, there is a decrease of 140 thousand Korean won in monthly income. This decrease is considerably greater than the decrease of 42.83 thousand won observed for young individuals.

It is understandable to assume that small and medium-sized businesses would have reduced the salaries they pay to their employees after the implementation of the Youth Tomorrow Chaedum Deduction, since businesses contribute to the savings fund to some extent. However, it would be interesting to see in a follow-up study whether this is associated with a significant reduction in income for those who have been with the company for more than two years.

4.2 Conditional average treatment effect

The preceding analysis focuses on the average treatment effect by the DiD method, but it is important to recognize that there is potentially hidden heterogeneity within this average and dig deeper. To address this issue, the Causal forest method estimates the conditional average treatment effect for each observation based on covariates, and uses the results from CATE to suggest which subgroups should be the focus of policy implementation. Specifically, from 2023, the Youth Tomorrow Chaeum Deduction Policy exclusively targets the manufacturing and construction industries from 2023 [Ministry of Employment and Labor, 2023]. Hence, the focus of this paper is to identify differences in treatment effectiveness across different categories, especially industry sectors.

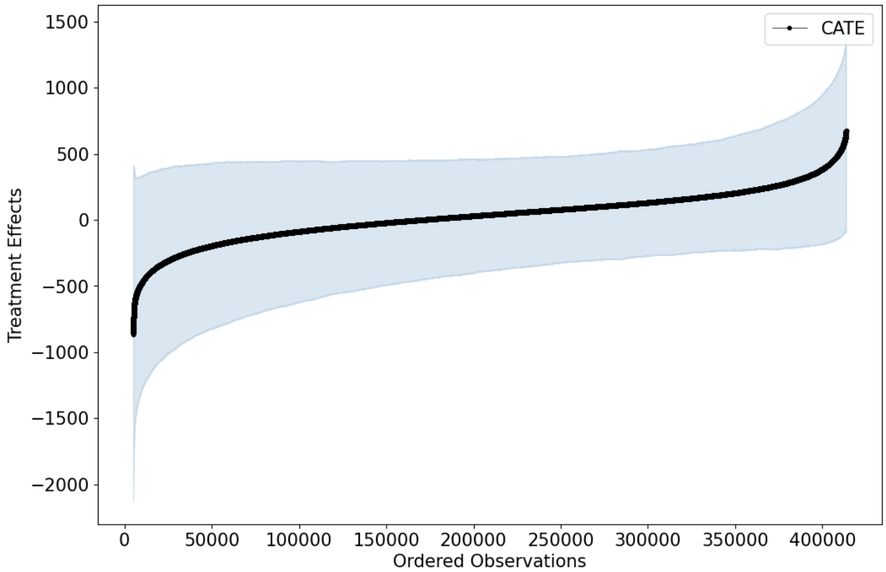

Figure 4.2: Observations sorted by treatment effect level

Note: Plot of the CATE and confidence intervals from the causal forest mode. Observations are sorted by value of treatment effect. The CATE is computed using the rolling mean method with a window size of 10,000.

Figure 4.2 displays The distribution of estimated treatment effects generated by the causal forest. Observations are sorted by the value of the treatment effect. When viewed horizontally, the S-shaped line of CATE values shows most treatment effects clustered around zero, with negative treatment effects on the left and positive treatment effects on the right. By anticipating the presence of disparities between the most and least affected observations, it is possible to compare the average characteristics of these groups. This comparison can help identify potential factors contributing to the observed heterogeneity.

A comparison of the estimated positive CATE groups clustered at the right end (20% most affected) of the S-shaped line with the negative CATE groups at the left end (20% for least affected) is shown in Table 4.3 with ATE. The ATE value is 25.25 which is larger than Difference-in-Differences result. The highest affected group has a CATE value of 320.82 and the least affected group has a negative value of -304.02. From the table, it can be observed that there are both significantly negative values and significantly positive CATE values.

Table 4.3: CATE results

	20% Least	ATE	20% Most
CATE	-304.02	25.25	320.82

When examining CATE by subgroup, the analysis aims to identify the demographics where policy focus should be directed. Figures 4.3 through 4.6 show the differences in the distribution of the heterogeneous effect for different demographic subgroups. However, it is important to consider a caveat to this interpretation. Some groups may exhibit larger CATE values compared to others, but it is crucial to acknowledge that these groups may have already been associated with Small and Medium Enterprises (SMEs) for a longer duration without the policy intervention. This view of the policy needs to be taken into account when evaluating the findings and determining the appropriate policy actions.

Figure 4.3 illustrates a kernel density plot of the treatment effects by gender. The distribution clearly shows that men have a larger distribution of CATE values than women. This means that the policy has a more positive effect on men than women when the policy is given.

Similarly, this approach is applied to education levels in Figure 4.4. All levels except Master's degree or over have a positive CATE value above zero, and the average value of CATE increases as the level of education rises. This shows that most people with a bachelor degree have the largest positive effect than other

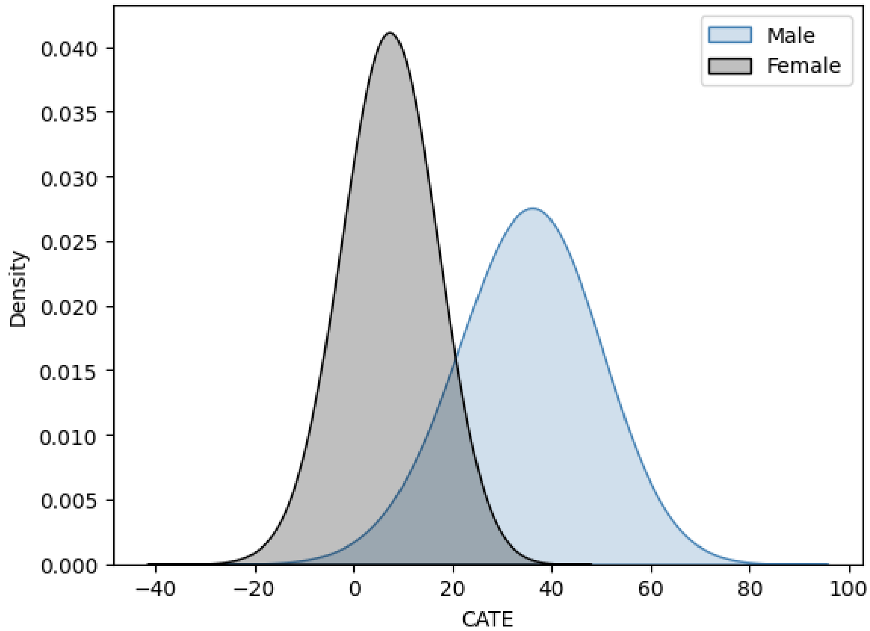

Figure 4.3: CATE distribution by gender

Note: Each distribution represented in the plot corresponds to a kernel density estimation of individual treatment effects. These treatment effect predictions are derived from the causal forest algorithm. The CATE is computed using the rolling mean method with a window size of 1000.

group. From the perspective that the effect of the policy is most effective for college graduates, it seems that the policy has a positive impact on improving the tenure of young employees of small and medium-sized enterprises who are college graduates. This is one of the main goals of the Youth Tomorrow Chaeum Deduction policy.

As the Youth Tomorrow Chaeum Deduction is largely divided by industry, it is important to identify heterogeneous treatment effects by industry. In addition, if CATE is also identified by occupation category, more detailed policy targeting is possible. Figure 4.5 and 4.6 are box plots which show the distribution of the predicted CATEs for individuals by industry and classification of occupations.

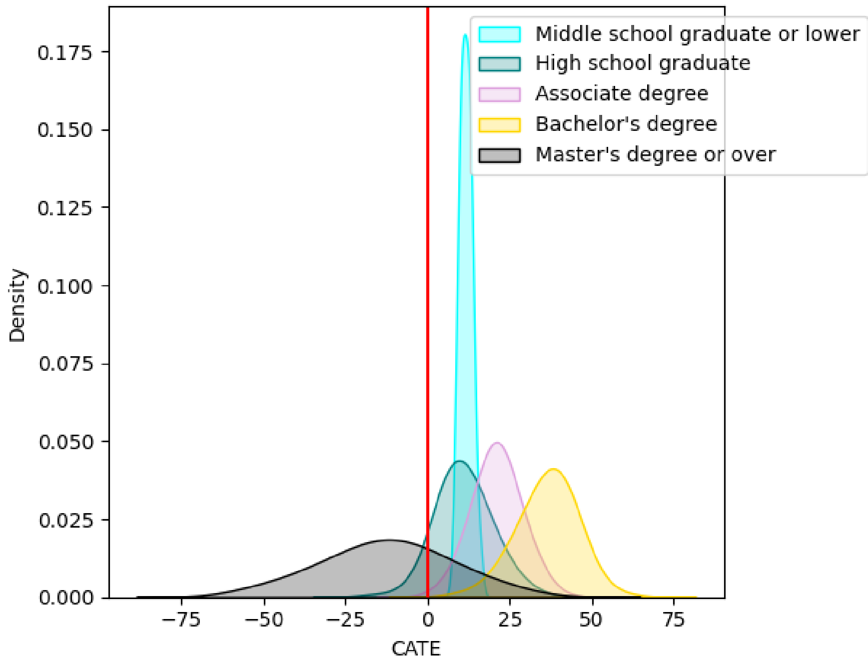

Figure 4.4: CATE distribution by education level

Note: Each distribution represented in the plot corresponds to a kernel density estimation of individual treatment effects. These treatment effect predictions are derived from the causal forest algorithm. The CATE is computed using the rolling mean method with a window size of 1000.

Width is proportional to size of group.

The boxplot in Figure 4.5 depicts the distribution of CATE predictions for individuals by industry. This figure captures the heterogeneity of predicted CATE by industry. From Water, sewage and waste treatment, raw material recycling, to Accommodation and F&B Business, most individuals in these industries have positive values. Looking at manufacturing and construction, which are the focus of the policy starting in 2023, all individuals working in construction have a positive effect greater than zero. For manufacturing, there is an outlier CATE with a value below zero, but the entire distribution except for that value has a positive effect. While it is true that certain industries such as the Health and social welfare

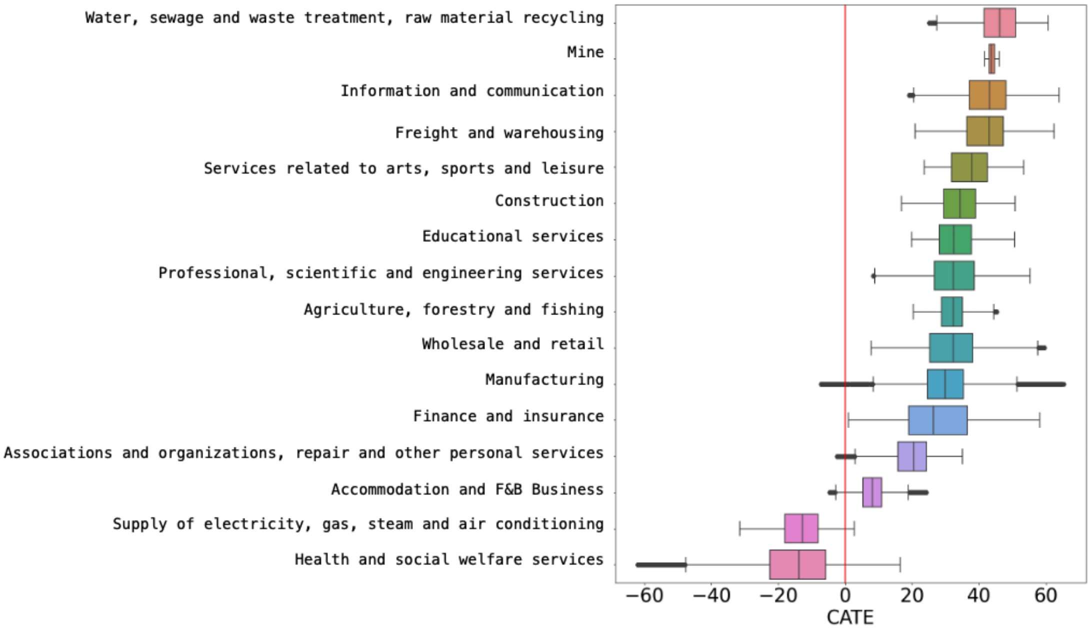

Figure 4.5: CATE by industry

Note: Each boxplot illustrates the CATE derived from the causal forest. The CATE is computed using the rolling mean method with a window size of 1000.

services industry and the Supply of electricity, gas, steam and air conditioning industry have negative CATE distributions less than zero, it is important to note that even within these industries there are individuals with positive CATE values close to +20. What is also notable about this figure is that most industries, including manufacturing and construction, have positive CATE values and seem to be beneficial for policy, so it may be worth considering implementing policies in these industries as well. By identifying the demographic characteristics of individuals with high CATE values within each industry, it is possible to target policies more specifically. This would be more efficient than drastically reducing the number of industries covered at once.

Furthermore, because occupation is categorizable, it can play an important role

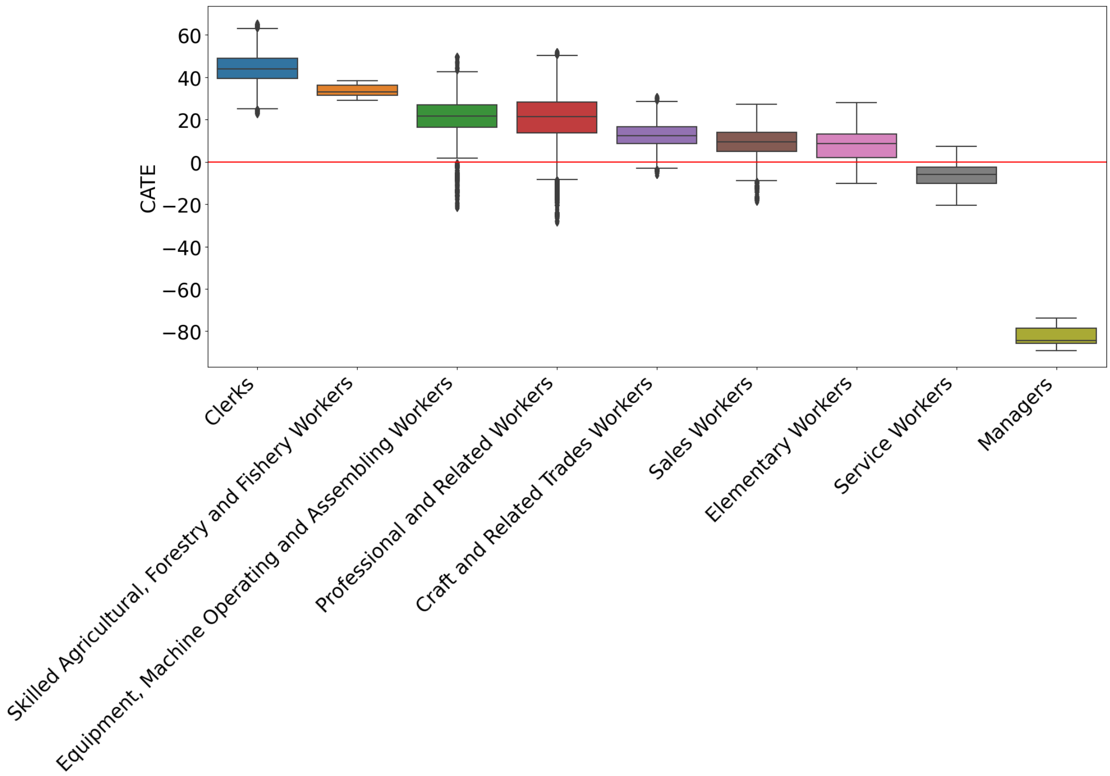

Figure 4.6: CATE by classification of occupations

Note: Each boxplot illustrates the CATE derived from the causal forest. The CATE is computed using the rolling mean method with a window size of 1000.

in policy eligibility criteria. Figure 4.6 presents a boxplot depicting the CATE values stratified by occupation. The graph clearly demonstrates a discernible heterogeneous effect across different occupations. Notably, managers exhibit a notably strong negative CATE value, indicating that the Youth Tomorrow Chaeum Deduction policy has no discernible impact on this particular occupational group. Also, most of the service workers display a negative effect. However, there is also a big gap between service workers and mangers. This result implies that the Youth Tomorrow Chaeum Deduction policy was particularly ineffective for managerial positions.

Given the policy, the Clerks have the highest degree of treatment effects among all occupations. The next is skilled agricultural, forestry and fishery workers. This is followed by equipment, machine operating and assembling workers, professional and related workers with similar distributions of CATE values. This observation suggests that if there are limitations in the policy budget, prioritizing investments in clerks while reducing investment for managers would be prudent.

To uncover the factors driving the differentiation, the SHAP (SHapley Additive exPlanations) method is used. SHAP presents the main drivers of the effect heterogeneity captured by the model and the importance of the features. By listing the feature importance, it is possible to determine variables to pay attention to [Lundberg and Lee, 2017].

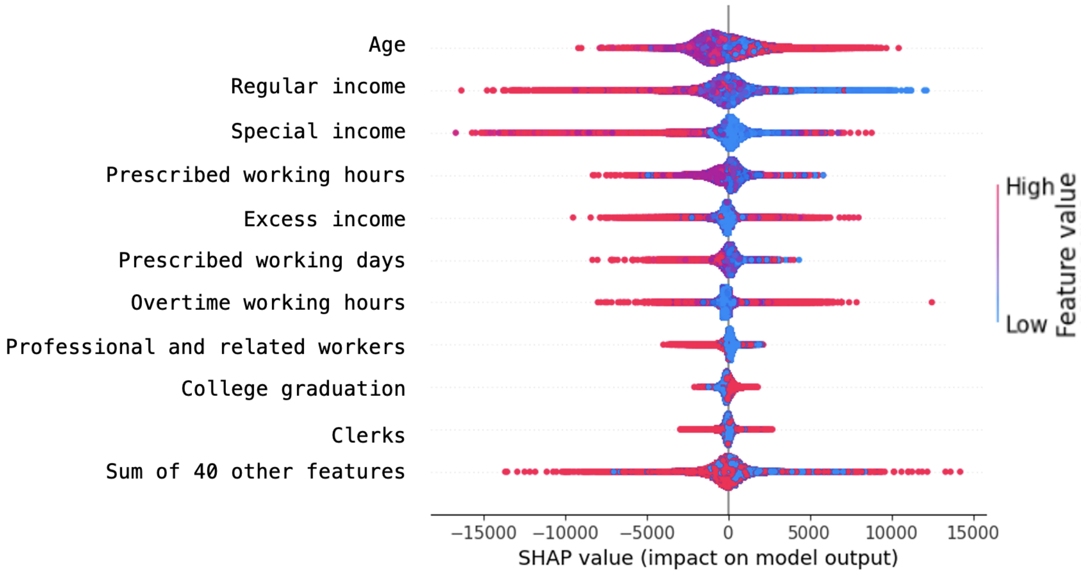

Figure 4.7: Summary plot of SHAP values

Figure 4.7 displays a summary plot of the SHAP values, and Figure 4.8 depicts the average of the absolute SHAP values for each feature, listed in order. Table

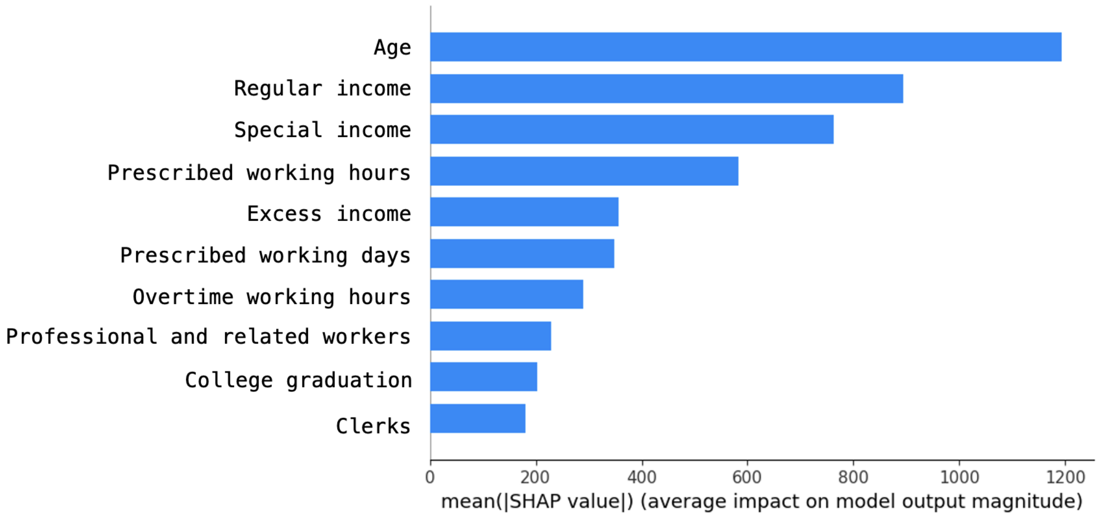

Figure 4.8: Summary plot of mean SHAP values

Note: The average impact on model output magnitude

Table 4.4: CATE differences in feature importance

Feature name	20% Least	20% Most
Age	30.10	33.39
Regular income	2751.89	2992.77
Special income	4773.45	5511.64
Prescribed working hours	162.72	164.96
Excess income	196.11	194.62
Prescribed working days	20.40	20.63
Overtime working hours	11.26	9.93

4.4 lists the top 20% and bottom 20% CATE values of the variables in Feature importance.

The highest important covariate (feature) is the age of the employee. This is natural because older employees tend to have more experience. It is followed by regular income, special income working, prescribed working hours, excess income, prescribed working days, overtime working hours, professional and related workers, college graduation, clerks. For regular income, the blue dots are distributed over positive values, suggesting that the feature was important when the average causal effect was negative. However, upon the CATE differences presented in Table 4.4, it is evident that the 20% group with the highest value demonstrates a higher CATE value compared to the 20% group with the lowest value. SHAP results that are opposite of expected values can be assumed to be due to the fact that this analysis does not call the tune of the forest before fitting. That might choose much better parameters for the dataset. Therefore, a more precisely tuned SHAP analysis reflecting hyperparameter tuning is left for future analysis.

And for college graduation, the red dots are distributed around positive values, suggesting that college graduation is featured as important when the average causal effect is positive. It accords with Figure 4.4 which illustrates that college graduates have the largest distribution of CATE values. The next most important variable is the clerk (white-collar). This is consistent with the CATE distribution plot by occupation in Figure 4.6 which shows that white-collar workers have the most heterogeneous positive treatment effects related to other groups. Based on these results, it seems more accurate to use the absolute values of the SHAP values to identify important features like Figure 4.8, rather than the summary plots that show the direction of feature importance, as shown in Figure 4.7.

This finding is applicable in identifying subgroups. The idea is to estimate CATE separately for different employee categories, such as college graduates and non-college graduates, and occupations classified as white-collar and other, based on feature importance. Conducting separate assessments for these subgroups can provide a more nuanced understanding of treatment effects, allowing for targeted interventions and policy recommendations.

Chapter 5

Conclusion and policy implication

How should one prioritize budget allocation for policies? Are there any positive or negative outcomes hidden in the average value that policy evaluations produce? To answer this question, this study focuses on deriving conditional average treatment effects using Causal Forest. A difference-in-differences is also performed to derive the average treatment effect.

This study focuses specifically on the performance of the Youth Tomorrow Chaeum Deduction policy. This policy aims to attract youth to small and medium-sized enterprises and induce them to work for a longer period of tenure. SMEs and young workers jointly accumulate funds and receive additional government support if they work for more than two years. At first, the difference-in-differences analysis demonstrates the advantages of the Youth Tomorrow Chaeum Deduction policy for companies by reducing labor costs and extending the average tenure of young individuals employed in small and medium-sized enterprises (SMEs) within the policy-applied industry. This finding indicates that young workers are more likely to remain employed for a longer period following the implementation of the policy. Moreover, from the perspective of young employees, the policy acts as a motivating factor to continue working for an extended duration at an SMEs due to the attractive financial incentive received after completing two years of employment. However, youth employees experience a decrease of 42.83 thousand Korean won in monthly income. This implies that the amount a company contributes to the deduction is ultimately linked to lower salaries for younger employees. Additionally, in the spillover context of individuals employed in SMEs for 24 months or more, no significant change in tenure is found. However, existing employees experience a decrease of 140 thousand Korean won in monthly income.

From the results, it can be concluded that the policy implementation leads to an extension in the tenure of young individuals working in SMEs. However, both young employees and existing workers experience a reduction in their monthly income. These findings suggest that the policy is most effective from the perspective of SME employers, as it contributes to increased retention of young workers while also resulting in cost savings in terms of monthly income expenditure.

The Causal Forest analysis reveals that the treatment effect of the Youth Tomorrow Chaeum Deduction policy was more pronounced among men compared to women. Additionally, the distribution of the treatment effect exhibits greater negative heterogeneity among individuals having a master's or higher degree or those in managerial positions, indicating that the policy was less effective for highly educated and managerial workers. However, college graduates have the greatest effect. Furthermore, a positive distribution of Conditional Average Treatment Effects (CATE) was observed across most industries, including manufacturing and construction, suggesting that reintroducing the policy in these industries could yield favorable outcomes.

Given the constraints imposed by political and budgetary considerations, targeting specific demographics that drive the heterogeneous effect would be a more efficient approach if it is not feasible to cover all industries. By identifying other characteristics associated with the heterogeneous effect and focusing solely on young individuals possessing those attributes, the policy can be effectively targeted and implemented.

Nevertheless, it is important to acknowledge a limitation in these analyses, as they do not account for the proportion of employees within each industry who have actually benefited from the Youth Tomorrow Chaeum Deduction. All observations in industries where the policy is applied are assigned to a treatment group, while observations in industries without the policy are designated as a control group. This approach aims to capture the overall effect at the industry level. However, the analysis would be enhanced by identifying employees who received the policy. This would enable the generation of more robust CATE values and a better understanding of the characteristics that drive heterogeneous treatment effects. Looking ahead, this Causal Forest methodology holds the potential for informing the beneficiary targeting and implementation of policies with limited budgets. By embracing machine learning-based approaches such as CF in future studies evaluating policies, policymakers will gain the ability to distinguish heterogeneous effects across demographic subgroups. This will enable them to construct a more solid groundwork for making data-driven decisions in public policy.

REFERENCES

Susan Athey and Stefan Wager. Estimating treatment effects with causal forests: An application. *Observational Studies*, 5(2):37–51, 2019.

Susan Athey, Julie Tibshirani, and Stefan Wager. Generalized random forests. 2019.

Leo Breiman. Random forests. *Machine learning*, 45:5–32, 2001.

Raffaello Bronzini and Paolo Piselli. The impact of r&d subsidies on firm innovation. *Research Policy*, 45(2):442–457, 2016.

Victor Chernozhukov, Denis Chetverikov, Mert Demirer, Esther Duflo, Christian Hansen, Whitney Newey, and James Robins. Double/debiased machine learning for treatment and causal parameters, 2017.

Jonathan MV Davis and Sara B Heller. Using causal forests to predict treatment heterogeneity: An application to summer jobs. *American Economic Review*, 107 (5):546–550, 2017.

Jonathan MV Davis and Sara B Heller. Rethinking the benefits of youth employment programs: The heterogeneous effects of summer jobs. *Review of Economics and Statistics*, 102(4):664–677, 2020.

Huseyin Gulen, Candace Jens, and T Beau Page. An application of causal forest in corporate finance: How does financing affect investment? *Available at SSRN*, 2020.

Ian Hoffman and Evan Mast. Heterogeneity in the effect of federal spending on local crime: Evidence from causal forests. *Regional Science and Urban Economics*, 78:103463, 2019.

Daniel Jacob. Cate meets ml: Conditional average treatment effect and machine learning. *Digital Finance*, 3(2):99–148, 2021.

Nazanin Khazra. Heterogeneities in the house price elasticity of consumption. *Available at SSRN 3483279*, 2019.

Yubin Kim. Analyzing the performance of the youth tomorrow chaeum deduction Focusing on dropouts and maturities. *Labor Review Journal*, pages 71–84, 2020.

Christopher R Knittel and Samuel Stolper. Using machine learning to target treatment: The case of household energy use. Technical report, National Bureau of Economic Research, 2019.

Korean Statistical Information Service. Economically active population survey. `https://kosis.kr/statHtml/statHtml.do?orgId=101&tblId=DT_1DA7002S&conn_path=I2`, 2023. Accessed: 2023, February 28.

Noemi Kreif, Andrew Mirelman, Rodrigo Moreno Serra, Taufik Hidayat, Karla DiazOrdaz, and Marc Suhrcke. Who benefits from health insurance?: Uncovering heterogeneous policy impacts using causal machine learning. 2020.

Michael Lechner. Causal machine learning and its use for public policy. *Swiss Journal of Economics and Statistics*, 159(1):1–15, 2023.

Sunghee Lee. The youth tomorrow chaeum deduction policy, employment effect and improvement plan of youth intern program. *Monthly Labor Review*, 156: 46–58, 2018.

Scott Lundberg and Su-In Lee. A unified approach to interpreting model predictions, 2017.

Microsoft. EconML: A python package for estimation and inference of heterogeneous treatment effects. `https://econml.azurewebsites.net/spec/estimation/dml.html#dmluserguide`, 2023a. Accessed on 11th June 2023.

Microsoft. CausalForestDML. `https://econml.azurewebsites.net/_autosummary/econml.dml.CausalForestDML.html#econml.dml.CausalForestDML`, 2023b. Accessed on 11th June 2023.

Ministry of Employment and Labor. 100,000 young people are nurturing their hopes for tomorrow with the youth tomorrow chaeum deduction, August 2021. URL http://www.moel.go.kr/news/enews/report/enewsView.do;jsessionid=awPilIXDpkAk4Q1Ds309ZEqkZOamJXaknMMOqTezF30qM1papLSIAo77ZNeV4mFs.moel_was_outside_servlet_www2?news_seq=12625. Press release.

Ministry of Employment and Labor. Implementation guideline for the 2022 youth tomorrow chaeum deduction, January 2022.

Ministry of Employment and Labor. Implementation Guideline for the 2023 Youth Tomorrow Chaeum Deduction, February 2023.

Ministry of Strategy and Finance. Youth Tomorrow Chaeum Deduction, Specialized where needed, such as manufacturing. https://www.korea.kr/news/policyNewsView.do?newsId=148906196, 2023. Accessed on June 13, 2023.

Ministry of Employment and Labor. Youth tomorrow chaeum deduction. https://www.moel.go.kr/policy/policyinfo/young/list1.do, 2023. Accessed: 2023, February 23.

Chungryeol Park. Operation status and improvement tasks of tomorrow chaeum deduction for young employees. Issues and Perspectives 2000, National Assembly Research Service, 2022.

Donald B Rubin. Randomization analysis of experimental data: The fisher randomization test comment. *Journal of the American statistical association*, 75 (371):591–593, 1980.

Igor Shuryak. Analysis of causal effects of 137cs deposition on 137cs concentrations in trees after the fukushima accident using machine learning. *Journal of Environmental Radioactivity*, 264:107205, 2023.

Robert Tibshirani. Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*, 58(1):267–288, 1996.

Stefan Wager and Susan Athey. Estimation and inference of heterogeneous treatment effects using random forests. *Journal of the American Statistical Association*, 113(523):1228–1242, 2018.