The Impact of Gap Years on Post-Graduation Income

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Abstract

This paper investigates the relationship between taking a gap year during university and post-graduation income. Using data from the National Longitudinal Survey of Youth 1997 (NLSY97), we find a significant negative association between gap years and earnings after graduation. On average, each year of gap taken correlates with a 4% reduction in post-graduation income. The analysis shows that these effects are not homogeneous: women and individuals from minority backgrounds are disproportionately affected, experiencing even larger income penalties. We apply causal forest methods to explore heterogeneous treatment effects, identifying subgroups that bear a heavier economic burden for taking a gap year. The findings align with existing literature on delayed graduation and labor market outcomes who observe similar penalties for gap years. Our results suggest that educational institutions should provide more comprehensive support for students considering gap years, especially during periods of economic instability such as recessions. Furthermore, policymakers should consider targeted interventions to mitigate these long-term financial consequences.

Keywords: gap year, post-graduation income, heterogeneous treatment effects, causal forest, labor market outcomes

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1 Introduction

The Covid-19 pandemic was incredibly challenging for college students. When schools shut down and transitioned to remote learning, many students opted to take time off, either a gap year or a gap semester. Postsecondary enrollments dropped by 2.5% in the fall of 2020, nearly twice the rate of decline from a year earlier, according to the National Student Clearinghouse Research Center's December 2020 report. The primary driver of this decline was a 3.6% drop in undergraduate enrollment.

Students made the decision to take time off for various reasons. Many could no longer afford to enroll due to financial pressures brought on by the pandemic. Others did not want a diminished college experience, as most universities had shifted online, and many hallmark aspects of higher education—internships, jobs, and study abroad opportunities—were canceled. For some, the emotional and psychological toll of the pandemic led to burnout, prompting them to step away from their studies temporarily. Although students had personal motivations, a critical question remains: is taking a gap semester or year truly a decision that leads to long-term benefits, particularly in terms of career outcomes and income? This paper seeks to examine that decision and assess the impact of taking a gap year on post-graduation income using empirical analysis.

The idea of taking a gap year, however, is not limited to the pandemic. In past economic downturns and recessions, students have made similar choices to avoid entering a struggling labor market. The logic is that by delaying graduation, they may avoid a period where job opportunities are scarce and wages are lower. While there are anecdotal claims that taking time off allows students to gain valuable experience and clarity about their career paths, the empirical evidence on the long-term impact of these decisions remains mixed. In this context, understanding the economic consequences of taking a gap year is particularly important as students weigh their options during periods of uncertainty.

A key aspect of this analysis is the exploration of *heterogeneous treatment effects*—how the impact of a gap year varies across different groups. For instance, the effect of taking a gap year may differ significantly by gender, race, or academic performance. Traditional econometric methods often focus on estimating an average treatment effect (ATE), but this approach can mask important variations in how different individuals experience the effects of taking time off. To address this limitation, we apply *causal forests*, a machine learning technique designed to estimate *Conditional Average Treatment Effects (CATE)*, which allows us to identify how the effects of taking a gap year differ across subpopulations.

Causal forests, introduced by Wager and Athey (2018), build on the random forest algorithm but are specifically designed for causal inference. Unlike conventional regression models, causal forests are non-parametric and are well-suited to capturing complex interactions between variables. By partitioning the data into subgroups, causal forests allow us to estimate treatment effects tailored to each individual, providing a more nuanced understanding of how the impact of taking a gap year varies based on an individual's characteristics, such as their academic performance or socio-economic background. This approach enables us to move beyond the average treatment effect and explore the full spectrum of possible effects, which is critical for policy interventions aimed at different segments of the population.

In this paper, we use data from the NLSY97 to explore the heterogeneous effects of taking a gap year on post-graduation income. Our findings suggest that there is a negative correlation between taking a gap and post-graduation income, a trend that persists for several years after graduation. However, this effect is not uniform. Using the causal forest methodology, we uncover significant heterogeneity in the treatment effects, with certain subgroups experiencing a much larger income penalty than others. These findings provide important insights into the decision-making process for students contemplating whether to take a gap year, particularly in times of economic uncertainty.

2 Literature Review

There are several papers that assess the effect of taking time off from college on early labor market outcomes of university graduates. Aina and Casalone (2020) use the AlmaLaurea Consortium dataset, which has a sample of 24 universities, and find that delayed graduation reduces the chances of finding a job by 0.8% for each additional year spent. This penalty eventually disappears for men but persists for women, although over time, the severity decreases. The reason cited is that women are seen as a higher risk due to potential motherhood, leading employers to prefer hiring younger women or women who are the same age as their male counterparts. Women with lower academic records face a greater penalty for delayed graduation than their male counterparts. Although both genders experience adverse effects, the impact is more severe for women, resulting in a monthly earnings penalty of about nine euros ($10.96) on average, which becomes eight euros ($9.74) for men and ten euros ($12.18) for women.

One exception to these findings is for those pursuing STEM degrees. Individuals in non-STEM fields are less likely to find a job if they do not complete their studies in the minimum period, possibly due to an oversupply of graduates in these fields relative to demand. Delayed graduation allows for the gaining of more experience, which can increase marketability. In conjunction with high final grades, it was found that STEM graduates did not face any penalization for extended time to degree completion. However, even among STEM students, females are disproportionately affected, with a persistent gap in employment outcomes.

Another paper written by Holmlund et al. (2008) used the Swedish IFAU database as well as national census data to estimate the effects of earnings due to gap years between high school and university enrollment. They sought to answer whether taking a gap year is wasteful or productive and whether policies should be put in place that make gap years to university enrollment so costly. In their study, they found that one additional gap year is associated with 0.56 additional years of work before university, 0.05 additional years of work during university, and 0.75 fewer years of work after university. Altogether, the data showed that a gap year reduces the total work experience of an individual. It shifts more of the work experience to before university and reduces the work experience after university, which could decrease the value of post-university work experience. Moreover, they found that it changes the timing of inactivity by increasing inactivity before studies and then reducing it afterward.

The concluding findings among Swedish university entrants around the turn of the century reveal that 25% of the sample took two to four gap years, while 40% took more than five gap years. The researchers observed that these gap year patterns were not unique to Sweden, but their findings pointed to negative effects on lifetime earnings and wages at ages 30 to 40. One additional gap year was associated with a 2% lower earnings and wage rate at age 35, though the effects declined and eventually disappeared by age 40.

Additionally, Choi et al. (2019) examine the impact of financial crises on gap year decisions. Using 20 waves of the Korean Labor and Income Panel Study, they find that men who graduate during a recession face significant reductions in employment, earnings, marriage, and other social outcomes for up to 12 years after graduation. Men who graduate during recessions are less likely to find stable employment because they either lack the necessary skills for the job market or employers are unwilling to pay them what they believe they are worth. This prolonged impact of economic recessions exacerbates the penalties associated with taking gap years during periods of economic downturn.

Building on research about recession impacts, Oreopoulos et al. (2012) provide compelling evidence from a 30-year longitudinal study showing that graduating in a recession can have persistent, long-term effects on career trajectories. Using U.S. Social Security Administration data, they find that college graduates who enter the labor market during a recession face initial annual earnings losses of 6-7% for each percentage point rise in the unemployment rate. While these losses diminish over time, they still experience earnings penalties even 15 years after graduation, with total lifetime earnings losses estimated at about 100,000 dollars in present value. The study reveals that recession graduates often start at lower-paying, lower-quality firms and experience reduced mobility between jobs, leading to slower career progression. These findings complement Choi's work by demonstrating that the negative impacts of graduating during economic downturns are not limited to specific regions or time periods but represent a broader pattern across different economic contexts.

Several studies have explored the role of human capital theory in the context of career breaks. Blinder and Weiss (1976) suggest that interruptions in education may lead to slower accumulation of industry-specific skills, which can hinder career progression and result in long-term wage penalties. For graduates who take a gap year, this can result in lower initial wages and fewer job opportunities in competitive industries.

The literature on heterogeneous treatment effects also provides insight into the varying impacts of taking a gap year on different subgroups. Wager and Athey (2018) introduce the causal forest methodology to estimate heterogeneous treatment effects, allowing for a more nuanced understanding of how the impact of a gap year differs across subpopulations. Their analysis highlights the importance of considering academic performance, gender, and race when assessing the long-term consequences of a gap year. Similarly, Davis and Heller (2017) apply causal forests to study treatment heterogeneity in a youth employment program, demonstrating that causal forests can flexibly identify subpopulations that benefit or suffer disproportionately from interventions such as gap years.

These findings emphasize the need for policy considerations that account for the complex interactions between individual characteristics and career interruptions.

Finally, Gibbons and Waldman (2006) discuss the potential benefits of gap years, arguing that time off can allow students to gain a clearer understanding of their career goals or acquire additional skills, thus making them more competitive in the labor market. However, empirical evidence supporting these benefits is limited, and the negative effects, particularly in terms of wages and job opportunities, tend to outweigh potential advantages.

In this paper, we build on this body of research by using the causal forest methodology to explore the heterogeneous effects of taking a gap year on post-graduation income. Our contribution lies in identifying how specific subgroups, such as women, minority groups, and those with lower academic performance, are disproportionately affected by gap years, providing a more comprehensive understanding of the long-term implications of taking time off from education.

3 Data and Descriptive Statistics

For this study, we used the NLSY97 dataset, a nationally representative sample of youth born between 1980 and 1984 who were living in the United States at the time of the initial survey. The NLSY97 has collected information about the youth and their families annually from 1997 until 2011 but switched to a biannual data collection from 2011 until 2017. The sample members graduated from high school in the late 1990s and early 2000s, and most graduated from college in the mid-2000s.

One strong case for using NLSY97 is the data it provides regarding the monthly enrollment status of college students from 1997 until 2017. In addition, the NLSY97 also provides the graduation date of students. By gauging each observation's monthly enrollment and the date they graduated as the end reference, we can track each student's number of months not enrolled and essentially how much more time students took to graduate from college. In addition, the NLSY97 contains the AFQT scores of the individuals, and we will be able to control for the scores in case the scores have correlation to income.

In addition, the NLSY97 contains income data of individuals for all the waves the survey was collected. Our primary interest is to find the effect that a longer time to graduate than usual has on the income variable measured in dollars. Thus, by using the income as a dependent variable and the created variable, added time to graduate, as an independent feature, we can capture the correlation between income and added time to graduate by controlling for other factors.

To closely analyze the variables with discrete values, we relaxed the variables by changing each discrete variable into a binary variable. In addition to relaxing the discrete variables, we included a log of income as the dependent variable since income is skewed where individuals who make a large amount of income pull the mean much higher than the median.

The table below summarizes the variables and data for the year 2017, which contains the most up-to-date information about the individuals. Table 1 summarizes the original

Table 1: Original NLSY97 variables selected from NLSY investigator

Variable Name	Description
PUBID	A unique identifier number for each observation.
SCH_COLLEGE_STATUS - SCH_COLLEGE_STATUS	Monthly college enrollment from 1997 - 2018.
CVC_BA_DEGREE_XRND	NLSY created variable reporting the date each observation received their bachelor's degree.
KEY_SEX	Discrete from 1 to 2, where 1 represents male and 2 represents female.
KEY_BDATE	Continuous year data ranging from 1980 – 1984.
KEY_RACE_ETHNICITY	Discrete value from 1 to 4, where Black, Hispanic, Mixed race (non-Hispanic), and non-Hispanic/non-Black are represented.
MAR_STATUS	Marital status and cohabitation status are reported using discrete values ranging from 0 to 5.
CV_INCOME_FAMILY	Annual family income from 1997 until 2017.
TTL INC WAGES, SALARY PAST YR - TTL INC WAGES, SALARY PAST YR 2017	Total income from wages, salary, and tips from the previous year, ranging from 1996-2016.
CV_HIGHEST_DEGREE_EVER	Highest degree achieved each year, from 1997 to 2018.

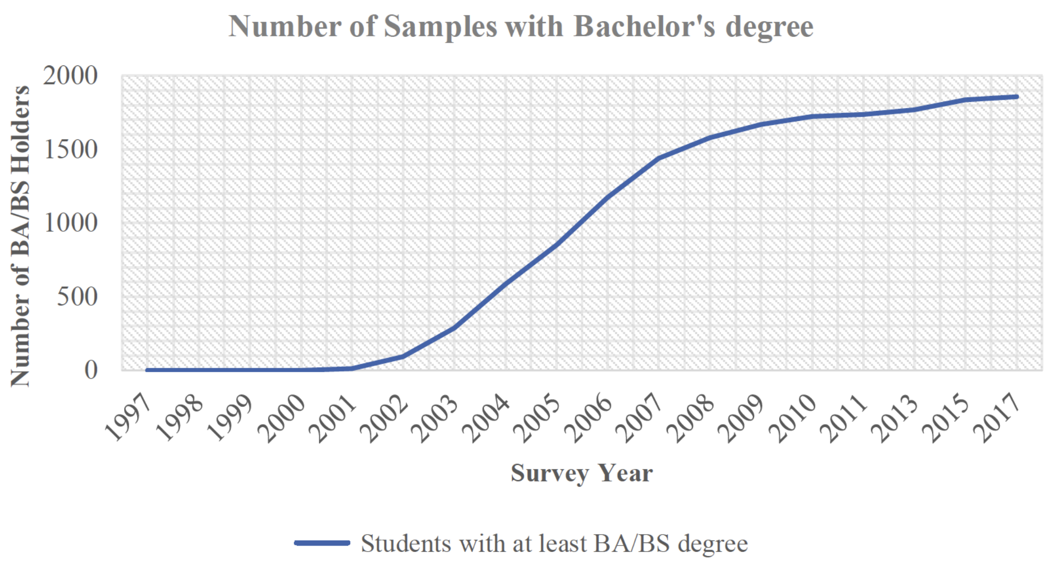

Figure 1: Number of Samples with at least a bachelor's degree 1997-2017.

variables from the National Longitudinal Survey of Youth (NLSY97) used in this analysis. The NLSY97 dataset provides rich data regarding students' educational paths, demographics, and family background. Each variable name is accompanied by a brief description. Notable variables include *SCH_COLLEGE_STATUS*, which captures the monthly college enrollment status of students from 1997 to 2018, and *CVC_BA_DEGREE_XRND*, which records the date each student earned their bachelor's degree. These variables serve as the basis for constructing additional variables such as *GapsTaken*, which tracks the

Table 2: Distribution of sample by gap time

Gap in Years	**Frequency**	**Percent**
0	1124	50.63
0 - 1	441	19.86
1 - 3	278	12.52
3 - 5	160	7.21
>5	217	9.77
Total	**2220**	**100**

time taken to complete a bachelor's degree, and for examining the effects of taking time off from school.

Table 2 shows the distribution of the sample based on the amount of time students took to graduate. The sample is divided into groups according to the "gap years" taken, which range from no gap to over five years. The column titled "Frequency" shows the number of students within each gap range, while the "Percent" column presents the corresponding percentage of the total sample. The table reveals that about half of the students (50.63%) graduated without taking any gap, while approximately 20% took a gap of one year or less. Around 30% of the sample took more than one year off from school. This information is crucial for understanding the time-to-degree dynamics and its potential impacts on post-graduation outcomes.

In this study, several new variables were created from the NLSY97 dataset to provide deeper insights into the relationship between gaps in education and income post-graduation. Table 3 lists the created and modified variables used in the regression analysis. For example, *GapsTaken* measures the additional time, in years, that a student took to graduate, while *logInc* represents the natural logarithm of yearly income, accounting for skewness in income data. Other important variables include demographic indicators like *Black*, *Hispanic*, *Male*, and *Female*, which help control for individual characteristics in the regression model. These variables are crucial for analyzing how different factors such as gender, race, and marital status influence the income trajectories of individuals who took gap years.

Table 4 provides summary statistics for the variables used in the analysis. It shows the number of observations (*Obs*), the mean, the standard deviation (*Std. Dev.*), and the minimum and maximum values for each variable. Key variables include *Yearly Income*, which captures the total yearly income for each individual, and *GapsTaken*, which measures the number of years a student took beyond the standard time to graduate. Demographic variables such as *Black*, *Hispanic*, and *Male* are also included, providing insights into the composition of the sample. The table highlights variability in income and other factors, offering a foundational understanding of the sample characteristics before proceeding with more advanced analysis.

Table 3: Created and modified variables description

Variable	Description
PUBID	A unique identifier number for each observation
logInc	Log of yearly income individuals earn
GapsTaken	Added time taken to graduate in years
AFQT scores	Armed Forces Qualification Test (AFQT) Percentile Score ranging from 0-100%
NeverMarriedNC	0 - non-never married not cohabitating individual 1 - never married and cohabitating individual
NeverMarriedC	0 - non-never married not cohabitating individual 1 - never married and cohabitating individual
Married	0 - individual is not married at the time of the data collection 1 - individual is married at the time of the data collection
Separated	0 - unseparated individual 1 - separated individual
Divorced	0 - not-divorced individual 1 - divorced individual
Widowed	0 - not widowed individual 1 - widowed individual
PotentialExperience	Continuous variable equal to age minus years of education minus 6
Black	0 - non-black individual 1 - black individual
Hispanic	0 - non-Hispanic individual 1 - Hispanic individual
MixedRace	0 - non-mixed race individual 1 - mixed race individual
White	0 - non-white individual 1 - white individual
Male	0 - non-male respondent 1 - male respondent
Female	0 - non-female respondent 1 - female respondent
BS	0 - does not hold bachelor's degree 1 - holds bachelor's degree

4 Empirical Strategy

Estimation of the returns to gap years raises all the usual problems encountered in the huge literature on returns to schooling (and the somewhat smaller literature on returns to experience). One potential problem is that gaps, like levels of schooling, are endogenously chosen by individuals, at least to some degree. A related problem is caused by the presence of omitted variables that affect education decisions as well as earnings. Measurement errors in schooling and work experience raise additional problems (although our data on education should be of high quality). This analysis relies on OLS estimates on NLSY data of several years, although with unusually detailed control variables for the

Table 4: Descriptive statistics (2017)

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Yearly Income	8984	28035.47	39228.38	-5	235884
GapsTaken	2220	1.332	2.380	0	14.83
Age	8984	34.99	1.396	33	37
Potential Experience	6193	11.16	2.769	2	15
log(Income)	5060	10.49	0.932	0.69	12.37
AFQT scores	8984	40.91	24.75	0	99
NeverMarriedNC	8984	0.18	0.385	0	1
NeverMarriedC	8984	0.079	0.270	0	1
Married	8984	0.285	0.452	0	1
Separated	8984	0.013	0.115	0	1
Divorced	8984	0.061	0.240	0	1
Widowed	8984	0.001	0.035	0	1
Male	8984	0.511	0.500	0	1
Female	8984	0.488	0.500	0	1
Black	8984	0.260	0.439	0	1
Hispanic	8984	0.212	0.408	0	1
Mixed Race	8984	0.009	0.096	0	1
White	8984	0.519	0.500	0	1

fields of education.

Let $Y_{i,j}$ denote individual i's annual earnings, where subscript j denotes the year the annual income was recorded. I estimate earnings at different years that NLSY97 surveys were taken, explaining earnings by a set of covariates and measure of gap years:

$$\ln(Y_{i,j}) = \alpha_j + \beta_j \cdot GapsTaken_{i,j} + \delta_j \cdot X_{i,j} + \lambda_j \cdot G_{i,j} + \theta_j \cdot M_{i,j} + \mu_{i,j} \tag{1}$$

The set of controls are represented by $X_{i,j}, G_{i,j}$, and $M_{i,j}$, where $X_{i,j}$ represents the set of controls related to education, specifically the variables *AFTQTscores*, the set of dummies for education level (i.e., MS, MD, PhD), and *PotentialExperience*. The set of variables related to demographics are represented by $G_{i,j}$, containing variables related to race such as *Black*, *Hispanic*, and *MixedRace*, as well as the gender dummy variable *Female*. The set of variables related to marital status are represented in the equation by $M_{i,j}$, which contains dummy variables such as *NeverMarriedC*, *Married*, *Separated*, *Divorced*, and *Widowed*. Our main variable of interest, *GapsTaken*, has the coefficient β_j, capturing the correlation between the number of years the student took a gap and the yearly income post-graduation.

We start our analysis after the year 2009, where most individuals have graduated and started earning yearly income. Our variable of interest, *GapsTaken*, is an exception to the time constraint since it is a summarized variable created using enrollment data before 2009, i.e., before the individuals graduated from college.

Although we have controlled for most of the variables that can potentially affect our *GapsTaken* coefficient, there are endogeneity concerns that give us reason not to causally interpret those coefficients. One reason for caution comes from the nature of the dataset, as mentioned in the previous section.

Another concern of endogeneity is simultaneity or simultaneous causality bias. This is certainly an issue in the model since the incentive to earn more income might motivate students to take gap years either to work and earn money or to take time off to invest in their skills to secure better income in the future. In either case, income becomes the motivation to take a gap semester or gap year. For these reasons, the estimated coefficients may be inconsistent and cannot be interpreted causally.

In addition to those concerns, there is also the issue of selection bias, which is mentioned briefly at the beginning of the section. Essentially, the observations of those who took gaps are not random; rather, individuals endogenously chose to take a gap or not. This creates biased estimators of earnings that cannot be exclusively related to taking a gap. That decision-making factor also influences the estimated coefficient, and causal interpretation of *GapsTaken* on income is biased.

Finally, there is the concern of omitted variable bias. We have unobservable characteristics that are hard to measure but are correlated with having taken a gap (or length of gap) and income after graduation. For instance, consider the variable that measures motivation: if a student is motivated to finish their schooling, then taking a gap may not be an option they consider. We are not controlling for those factors that are hard to measure and cannot be included in our analysis, which is why it is difficult to interpret our results causally.

Given these concerns, we focus our interpretation on the correlations between gap years and income, rather than claiming any strong causal relationship. Our results should be viewed as descriptive and indicative of potential trends rather than definitive proof of the effect of taking gap years on post-graduation earnings.

In this paper, we also apply the causal forest methodology to estimate Conditional Average Treatment Effects (CATE) of taking gap years on post-graduation income. Causal forests, a generalization of random forests for causal inference, allow us to flexibly estimate heterogeneous treatment effects across individuals based on their characteristics. Unlike traditional parametric models, causal forests are non-parametric and well-suited to capturing complex, non-linear relationships between gap years and income, and how these relationships vary by individual characteristics.

The primary advantage of causal forests is their ability to estimate how the treatment effect varies across subpopulations, conditional on a rich set of covariates such as gender, race, and academic performance. This allows us to move beyond the estimation of an overall average treatment effect (ATE) and instead focus on the variation in effects across different groups, providing a more nuanced understanding of how gap years impact income for different subgroups.

We began with a standard regression model to estimate the average treatment effect of taking gap years on income. The baseline model is specified as follows:

$$\log(Y_{it}) = \alpha + \beta \cdot GapsTaken_i + \delta X_{it} + \lambda G_{it} + \theta M_{it} + \mu_{it} \tag{2}$$

where $\log(Y_{it})$ represents the log-transformed income of individual i at time t, $GapsTaken_i$ is a binary indicator for whether the individual took a gap year, and X_{it}, G_{it}, and M_{it} are control variables for education, demographics, and marital status, respectively. The coefficient β represents the average effect of taking a gap year on income.

While this model estimates the ATE of gap years, we are interested in how this effect varies across individuals based on their characteristics. To capture this heterogeneity, we turn to the causal forest method, which estimates the CATE by conditioning on covariates.

Causal forests allow us to estimate CATE, which measures how the effect of taking gap years on income varies across individuals with different observable characteristics. The CATE for an individual i is defined as:

$$CATE_i = E[\log(Y_{it}(1)) - \log(Y_{it}(0)) | X_i = x] \tag{3}$$

where $\log(Y_{it}(1))$ represents the potential income if the individual took a gap year, and $\log(Y_{it}(0))$ represents the potential income if the individual did not take a gap year. The expectation is conditional on the individual's covariates, X_i, which include gender, race, AFQT scores, and marital status.

The causal forest method operates by growing a large number of decision trees, with each tree splitting the data to minimize the heterogeneity in treatment effects within each node. By aggregating the results from these trees, we obtain an individualized estimate of the treatment effect for each observation. This flexible approach allows us to detect how the effect of gap years varies across subgroups, identifying patterns that may not be visible using traditional regression models.

In our causal forest estimation, we include a comprehensive set of covariates to capture potential sources of heterogeneity in the treatment effect of gap years. These covariates include demographic factors such as gender, race, and age, as well as academic performance measures like AFQT scores and highest degree attained. We also control for socioeconomic background, including family income and parental education, as these factors may influence both the likelihood of taking a gap year and income post-graduation. Additionally, we account for marital status (e.g., married, separated, divorced) to control for its potential effects on income.

The rich set of covariates allows us to estimate how the treatment effect of gap years varies across different subpopulations. For example, causal forests can reveal whether the effect of taking gap years is more negative for women than for men, or whether individuals with lower AFQT scores are more adversely affected by taking time off from their studies.

To ensure the robustness of our CATE estimates, we implement several validation procedures. First, we use cross-validation to prevent overfitting and to assess the out-of-sample predictive performance of the causal forest model. Cross-validation helps confirm that the model generalizes well to new data and that our estimates of heterogeneous treatment effects are reliable. We also conduct a detailed subgroup analysis by examining CATE estimates across key subpopulations, such as gender, race, and academic performance groups. Additionally, we apply the honest inference framework proposed by Athey et al. (2019) to formally test the statistical significance of the heterogeneity in treatment effects.

The CATE estimates provide insights into how the effect of taking a gap year on income differs across individuals. For example, the causal forest may reveal that women experience a larger income penalty from taking gap years compared to men, or that individuals with lower AFQT scores face more severe labor market penalties for taking time off from their studies. These results highlight the importance of considering individual-level heterogeneity when evaluating the impact of gap years and suggest that the decision to take a gap year may have different consequences depending on one's demographic background and academic ability.

Our analysis with causal forests allows us to uncover nuanced patterns in the data that would be missed by standard regression approaches. By focusing on the heterogeneity in treatment effects, we provide a richer understanding of the impact of gap years on income and identify which groups are most affected by this decision.

By employing causal forests and estimating CATE, we are able to uncover the heterogeneous effects of gap years on post-graduation income. This approach allows us to move beyond average treatment effects and explore how different subgroups are affected by taking time off from their studies. Our findings provide valuable insights into the varying impacts of gap years and highlight the importance of tailoring educational policies to account for these differences across subpopulations.

5 Results

Using the regression model listed in the empirical strategy section, we ran the regression on five years of survey data from 2009 to 2017. The coefficients we obtained are negative, implying that there is a negative association between taking gap years and income post-graduation. On average, the estimated magnitude ranges from a 2.7% to 4.4% decrease in income for each additional year of gap taken, all else being equal. The coefficients are statistically significant at the 1% level. However, due to concerns mentioned in the empirical strategy, we cannot interpret these results causally.

The consistent results we see across the years suggest that even a few years after graduation, the reduction in income persists. Individuals do not seem to recover from

Variables	2009 (1)	2010 (2)	2013 (3)	2015 (4)	2017 (5)
GapsTaken	-0.0316***	-0.0274***	-0.0342***	-0.0440***	-0.0316***
	(0.00989)	(0.00990)	(0.00873)	(0.00957)	(0.00674)
NeverMarriedC	0.218***	0.133**	0.130**	0.135**	0.140**
	(0.0607)	(0.0607)	(0.0592)	(0.0628)	(0.0705)
Married	0.140***	0.175***	0.178***	0.131***	0.225***
	(0.0467)	(0.0471)	(0.0453)	(0.0475)	(0.0469)
Separated	0.272***	0.106	0.0523	0.519**	0.239
	(0.0952)	(0.303)	(0.0544)	(0.236)	(0.183)
Divorced	-0.199	-0.0407	0.0648	0.174**	0.190**
	(0.127)	(0.103)	(0.0965)	(0.0859)	(0.0781)
AFQTscores	0.00563*	0.00433	0.206**	0.0912	0.0184
	(0.0233)	(0.0391)	(0.0697)	(0.0511)	(0.0398)
Widowed	-0.497*	0.201	0.240	0.171	0.0713
	(0.286)	(0.241)	(0.181)	(0.131)	(0.0573)
PotentialExperience	0.0862***	0.00447	-0.102**	-0.0317	0.0286
	(0.0193)	(0.0290)	(0.0517)	(0.0654)	(0.0728)
PotentialExperience^2	-0.00358	0.00729	0.0119**	0.00382	-0.000884
	(0.00863)	(0.00717)	(0.00558)	(0.00524)	(0.00444)
Hispanic	-0.0585	-0.0177	0.00933	-0.00674	-0.0138
	(0.0815)	(0.0806)	(0.0700)	(0.0671)	(0.0597)
MixedRace	-0.134	0.228*	-0.160	0.0852	-0.0783
	(0.214)	(0.122)	(0.328)	(0.129)	(0.180)
White	0.0925*	0.0632	0.0532	0.0730*	0.0735*
	(0.0524)	(0.0562)	(0.0562)	(0.0448)	(0.0438)
Female	-0.136***	-0.173***	-0.248***	-0.357***	-0.373***
	(0.0407)	(0.0427)	(0.0406)	(0.0407)	(0.0356)
Constant	10.32***	10.22***	10.92***	11.25***	11.53***
	(0.183)	(0.211)	(0.149)	(0.156)	(0.252)
Observations	1,464	1,493	1,539	1,570	1,641
R-squared	0.068	0.04	0.059	0.09	0.147

Robust standard errors in parentheses

**** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Table 5: Regression results with *GapsTaken* as dependent variable for 2009-2017

the decrease in income within five years post-graduation. Additionally, the number of observations increases from 1,464 in 2009 to 1,641 in 2017. This increase is likely due to more individuals obtaining bachelor's degrees during this time period, as well as some students obtaining their degrees later than others.

There are several possible explanations for the negative correlation between taking gap years and post-graduation income. One potential explanation is that time taken off from college may not have been as productive as staying in school, leading to worse job outcomes after graduation. Another possibility is that employers may have a bias against students who take gap years, perceiving them as less productive or committed, which could impact their salary offers and career opportunities.

Variables	**2009 (1)**	**2010 (2)**	**2013 (3)**	**2015 (4)**	**2017 (5)**
GapsTakenDummy	-0.150***	-0.104**	-0.136***	-0.147***	-0.151***
	(0.0415)	(0.0425)	(0.0388)	(0.0397)	(0.0350)
NeverMarriedC	0.217***	0.131**	0.130**	0.135**	0.148**
	(0.0523)	(0.0605)	(0.0594)	(0.0630)	(0.0714)
Married	0.143***	0.174***	0.180***	0.140**	0.224***
	(0.0465)	(0.0471)	(0.0458)	(0.0630)	(0.0469)
Separated	0.260**	0.0981	0.0304	0.519**	0.269
	(0.109)	(0.303)	(0.0554)	(0.236)	(0.181)
Divorced	-0.183	-0.0410	0.0675	0.133***	0.174**
	(0.128)	(0.104)	(0.0967)	(0.0479)	(0.0778)
AFQTscores	-0.484*	0.193	0.259	0.169	0.0712
	(0.281)	(0.251)	(0.192)	(0.112)	(0.0571)
Widowed	-0.0733	0.111	0.240	-0.0377	-0.634***
	(0.174)	(0.226)	(0.181)	(0.0654)	(0.119)
PotentialExperience	0.0884***	0.00731	-0.0988*	-0.0260	0.0419
	(0.0195)	(0.0297)	(0.0518)	(0.0662)	(0.0729)
PotentialExperience^2	-0.00531	0.00606	0.0112**	0.00285	-0.00178
	(0.00870)	(0.00730)	(0.00560)	(0.00533)	(0.00443)
Hispanic	-0.0585	-0.0130	0.0150	0.00276	-0.00264
	(0.0815)	(0.0805)	(0.0705)	(0.0676)	(0.0597)
Mixedrace	-0.127	0.226*	-0.152	0.0976	-0.0681
	(0.210)	(0.123)	(0.330)	(0.133)	(0.179)
White	0.0929*	0.0654	0.0545	0.0455	0.0776*
	(0.0526)	(0.0562)	(0.0561)	(0.0454)	(0.0439)
Female	-0.133***	-0.173***	-0.244***	-0.355***	-0.369***
	(0.0408)	(0.0410)	(0.0406)	(0.0407)	(0.0356)
Constant	10.37***	10.25***	10.93***	11.26***	11.52***
	(0.187)	(0.216)	(0.149)	(0.157)	(0.253)
Observations	1,464	1,493	1,539	1,570	1,641
R-squared	0.071	0.04	0.059	0.083	0.147

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Table 6: Regression results with *GapsTakenDummy* as dependent variable for 2009-2017

In a subsequent analysis, we used the binary version of the *GapsTaken* variable to compare individuals who took a gap with those who did not. The results show a 10-15% decrease in income for those who took a gap year, on average, with statistically significant coefficients at the 1% level. While these results align with prior literature on the topic, we again caution against causal interpretation due to potential endogeneity.

Furthermore, we examined whether the decrease in income associated with taking a gap year affects male and female students differently. Our results indicate that women experience a larger income decrease (about 4%) compared to men (about 2%). This finding is consistent with the existing literature, which suggests that women are often penalized more heavily in the labor market, possibly due to biases related to motherhood and other factors.

Variables	**2017 (1) Women**	**2017 (2) Men**
GapsTaken	-0.0425***	-0.0225**
	(0.00798)	(0.00996)
NeverMarriedC	0.0373	0.242***
	(0.107)	(0.0875)
Married	0.0373	0.242***
	(0.107)	(0.0875)
Separated	0.363	0.205
	(0.432)	(0.155)
Divorced	0.407***	0.0762
	(0.0595)	(0.0708)
AFQTscores	0.201**	-0.0287
	(0.0879)	(0.0761)
Widowed	-0.0547***	-0.0829***
	(0.135)	(0.199)
PotentialExperience	-0.0773	0.156
	(0.0928)	(0.103)
PotentialExperience^2	0.00551	-0.0102
	(0.00552)	(0.00636)
Hispanic	0.00742	-0.00988
	(0.00557)	(0.00663)
Mixedrace	-0.122	0.217
	(0.209)	(0.296)
White	0.0398	-0.0174
	(0.0831)	(0.0830)
Constant	11.53***	11.05***
	(0.310)	(0.375)
Observations	735	906
R-squared	0.177	0.080

Table 7: Regression result for women and men, where (1) is for women, while (2) is for men with *GapsTaken* as the dependent variable

The results of the causal forest analysis show substantial heterogeneity in the effect of taking gap years on post-graduation income. This heterogeneity is evident when we examine the impact across different subgroups, particularly in relation to gender, race, and academic performance.

Variable	ATE Estimate
GapsTaken	-0.031***
	(0.008)
Observations	7707
R-squared	0.15

Table 8: Average Treatment Effect (ATE) of Gap Years on log Income

The Average Treatment Effect (ATE) of gap years on income is a 3.1% reduction, as shown in Table 4. This result aligns with other studies that examine the impact of career interruptions on income, where a similar income penalty is observed due to lost work experience and missed career advancement opportunities. For instance, Blau and Kahn (2006) discuss how career breaks, particularly for women, often result in wage penalties due to slower human capital accumulation during interruptions.

When we analyze the results by gender, we find that women experience a much larger income penalty from gap years compared to men. Table 9 shows the Conditional Average Treatment Effects (CATE) by gender:

Variable	Women	Men
GapsTaken	-0.045***	-0.020**
	(0.009)	(0.007)
Observations (Women)	3,503	
Observations (Men)		4,204
R-squared (Women)	0.16	
R-squared (Men)		0.14

Table 9: CATE Estimates by Gender for Gap Years on Income

As seen in Table 9, women face a 4.5% reduction in income from gap years, compared to only a 2% reduction for men. This gender disparity aligns with findings in the literature on the "motherhood penalty," where career interruptions for women, particularly due to family responsibilities, lead to more significant income losses than for men (Kleven et al., 2019). Women tend to face higher penalties due to differences in employment patterns, such as more frequent part-time work or concentration in lower-wage sectors (Zeytinoglu and Cooke, 2008).

The racial disparities in CATE are also notable. Table 3 presents the CATE estimates by race:

As shown in Table 10, Black and Hispanic individuals experience larger income penalties (-5.5% and -4.9%, respectively) compared to White individuals (-2.2%). These findings are consistent with research on racial wage gaps, where minorities often face systemic barriers in the labor market, leading to greater income losses during career breaks (Blau

Variable	White	Black	Hispanic
GapsTaken	-0.022**	-0.055***	-0.049**
	(0.011)	(0.013)	(0.011)
Observations (White)	3410		
Observations (Black)		2100	
Observations (Hispanic)			1950
R-squared (White)	0.13		
R-squared (Black)		0.15	
R-squared (Hispanic)			0.12

Table 10: CATE Estimates by Race for Gap Years on Income

and Kahn, 2006; Reilly and Wirjanto, 1999).

Academic performance, as measured by AFQT scores, also reveals significant heterogeneity in the impact of gap years on income. Table 4 shows the CATE estimates by academic performance:

Variable	Low AFQT	High AFQT
GapsTaken	-0.065***	-0.012*
	(0.016)	(0.009)
Observations (Low AFQT)	4878	
Observations (High AFQT)		3240
R-squared (Low AFQT)	0.16	
R-squared (High AFQT)		0.13

Table 11: CATE Estimates by Academic Performance (AFQT Quartiles) for Gap Years

Table 11 demonstrates that individuals in the lowest AFQT quartile experience a 6.5% income penalty from gap years, while those in the highest quartile face only a 1.2% penalty. This is consistent with research showing that individuals with lower academic ability face greater challenges in the labor market, particularly when career interruptions occur (Weinberger and Kuhn, 2010). In contrast, individuals with higher academic ability are better able to recover from these interruptions due to stronger labor market attachment and higher-paying opportunities (Mulligan and Rubinstein, 2008).

Finally, we observe significant interaction effects between gender and academic performance, as shown in Table 5:

Table 12 reveals that women with lower AFQT scores face the largest income penalties from gap years (-7.0%), while women with higher AFQT scores face a much smaller penalty (-2.0%). These findings suggest that women with lower academic performance are particularly vulnerable to long-term income losses from career interruptions. This aligns with research that highlights the "double disadvantage" faced by women with lower skills in the labor market, where both gender and skill level compound the negative effects of career breaks (Mulligan and Rubinstein, 2008; Blau and Kahn, 2006).

Variable	Low AFQT Women	High AFQT Women
GapsTaken	-0.070***	-0.020**
	(0.014)	(0.011)
Observations (Low AFQT Women)	2394	
Observations (High AFQT Women)		1680
R-squared (Low AFQT Women)	0.17	
R-squared (High AFQT Women)		0.13

Table 12: Interaction Effects of Gender and Academic Performance on Gap Years

The results from the causal forest analysis provide a nuanced understanding of the heterogeneous effects of gap years on income. These insights emphasize the importance of considering individual characteristics, such as gender, race, and academic ability, when assessing the long-term consequences of educational interruptions. Policymakers should take these differences into account when designing interventions aimed at mitigating the negative effects of career breaks for vulnerable populations.

6 Conclusion

In this paper, we have examined the correlation between taking a gap year during university and post-graduation income. Our analysis reveals a consistent negative association between the two, with a reduction in income of around 4% for each year of gap taken, ceteris paribus. These findings are supported by prior literature, including Holmlund et al. (2008), which shows similar income penalties for gap years.

Moreover, the results of our analysis reveal that the penalties for taking a gap year are more pronounced for women, who face higher income reductions than their male counterparts. This finding is consistent with studies such as Aina and Casalone (2020), who observed gender disparities in the economic outcomes associated with gap years. Choi et al. (2019) also found that economic recessions further exacerbate these income penalties, with men who graduate during a recession being less likely to find employment for up to 12 years post-graduation.

Although our analysis cannot provide a causal interpretation due to endogeneity concerns, the negative correlation observed should still be of concern for policymakers. Educational institutions may need to provide more comprehensive guidance for students considering gap years, particularly during periods of economic uncertainty. The development of advisory programs that emphasize the long-term economic consequences of taking a gap year could be beneficial for those who may be disproportionately affected, especially women and students from lower-income backgrounds.

Recent advances in machine learning, such as Causal Forests introduced by Wager and Athey (2018), provide new opportunities to explore treatment heterogeneity in this context. By applying these methods, future research could uncover which subgroups of students are most negatively affected by gap years, offering insights into more targeted policy interventions. For example, Davis and Heller (2017) demonstrate how Causal

Forests can identify subpopulations that benefit or suffer disproportionately from youth employment interventions. A similar approach could be applied to gap year decisions, providing a more granular understanding of the varying effects across different demographic groups.

One key direction for extending this research would be to incorporate a longitudinal component that tracks individuals' incomes and career outcomes over a longer period of time. While this study focused primarily on short-term post-graduation income, it is important to understand how the impact of taking a gap year evolves throughout the career lifecycle. Future studies could track individuals into their 40s or 50s to assess whether the income penalties observed immediately after graduation persist or diminish as workers gain more experience and develop new skills. This long-term perspective would offer valuable insights into whether gap years have a lasting impact or if their effects are temporary and fade over time.

Another avenue for future research would involve the interaction between gap years and other career-related decisions, such as pursuing further education (e.g., graduate studies) or entering entrepreneurship. Understanding how gap years influence decisions to pursue advanced degrees or start businesses would provide a more complete picture of how taking time off from university can shape an individual's career trajectory. This research could also examine whether gap years have different effects on income for those who choose different post-graduation paths. For instance, do gap years negatively affect those who transition into corporate jobs but offer advantages to those who pursue entrepreneurial ventures?

Moreover, future research could also explore the role of institutional factors, such as the quality of educational institutions or the availability of career services, in moderating the effects of gap years. Are students from more prestigious universities less affected by gap years? Does access to better career advising or stronger alumni networks mitigate the income penalties observed in this study? Investigating these questions could help identify institutional policies that can buffer the negative effects of gap years, offering strategies for universities to better support students during and after their time away from school.

Finally, incorporating a more robust qualitative component into future research could provide deeper insights into why individuals choose to take gap years and how they perceive its impact on their career and personal development. Surveys or interviews with students who took gap years could reveal valuable information about their motivations, experiences, and the benefits or challenges they encountered. Understanding the subjective experiences of these students could complement quantitative findings and offer a more holistic view of the gap year decision-making process.

In conclusion, while gap years offer students the opportunity to explore new experiences and develop personal insights, their economic costs in the form of reduced post-graduation income should not be ignored. The findings of this study, as well as those from the broader literature, highlight the need for further research into the heterogeneous effects of gap years. With the increasing availability of advanced machine learning techniques, future studies can develop more nuanced analyses that inform policies aimed at minimizing the negative economic impacts of gap years, ensuring better outcomes for all graduates. Understanding these long-term dynamics, especially when coupled with additional career and educational choices, will be key to providing students and policymakers with better tools to navigate the growing trend of gap years.

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