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# Effects of Educational Reforms in the Turkish context

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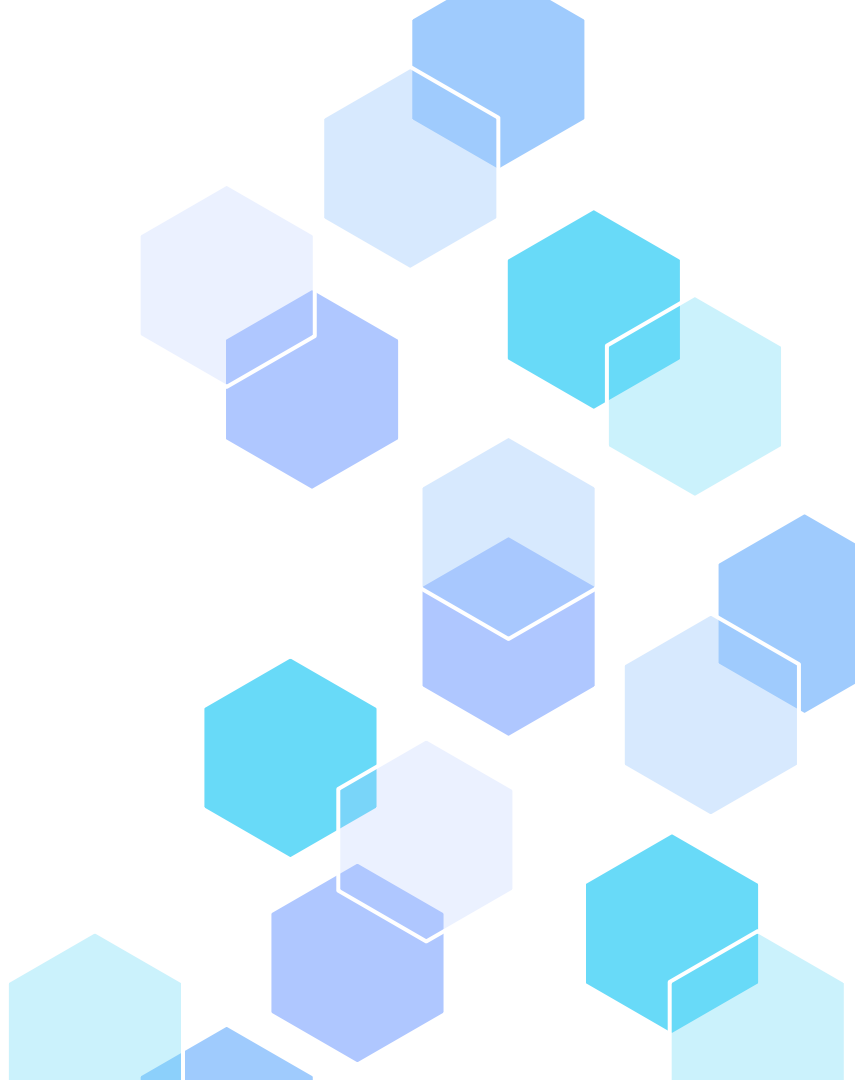
Interpretation of the  
results

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# 01

# Introduction

Background of study



# Introduction

In 2012 the Compulsory schooling mandate of Turkey increased schooling from 8 to 12 years. This policy change has impacted numerous amount of people when implemented. At the time many families argued that their children would not benefit from this additional years of education. Their argument was that their sons are better off working at an earlier age to gain **on-the-job training** which would earn them more money **compared to additional schooling**. Similarly these families argued that **their daughters should marry** and start a family **instead of having education**. While education and earnings have a multifaceted relationship, we investigate the causal aspects of this relationship using highschool completion as our primary treatment variable

# Where did we take the sample from?



**Turkey**

Turkish Labor data  
(2021-2022)

# Dataset Description

Labour Force Statistics Micro Data Set, 2022:

Compiled by the Turkish Statistical Institute (TurkStat), this dataset enables in-depth analysis of Turkey's labor market dynamics through the Household Labour Force Survey (HLFS).

- Scope and Methodology:
  - Geographic Coverage: All regions of Turkey, reported at NUTS1 and NUTS2 levels.
  - Sample Size: Quarterly surveys involving 58,560 households.
  - Collection Methods: Computer-Assisted Personal Interviewing (CAPI) and Computer-Assisted Telephone Interviewing (CATI).
- Key Variables:
  - Demographics: Age, gender, education level.
  - Employment: Job type, hours worked, labor force participation.
  - Unemployment: Job search activities, duration, and reasons.
  - Income: Monthly earnings and sources.
- Data Format: Delivered in CSV for use in statistical and econometric analyses.

# Background on Educational Reforms in Turkey

Turkey's educational reforms aim to strengthen the alignment between workforce skills and labor market demands, fostering human capital development and economic growth.

- Key Reforms:
  1. Compulsory Education Expansion:
    - Increased mandatory schooling years, boosting educational attainment and labor force participation among secondary and tertiary graduates.
  2. Vocational Education Modernization:
    - Improved alignment of technical education with market demands, reducing skill mismatches.
  3. Gender Equity in Education:
    - Enhanced female participation in education, leading to higher female labor force engagement.
  4. Lifelong Learning Initiatives:
    - Promoted reskilling and continuous education to meet evolving economic needs.

# Research question

“Did the 2012 reform extending compulsory schooling by four years in Turkey affect the wages in the labour market during 2021–2022 of students who completed their education under this system?”

If so, what the effect of this treatment?



# Contribution of the project

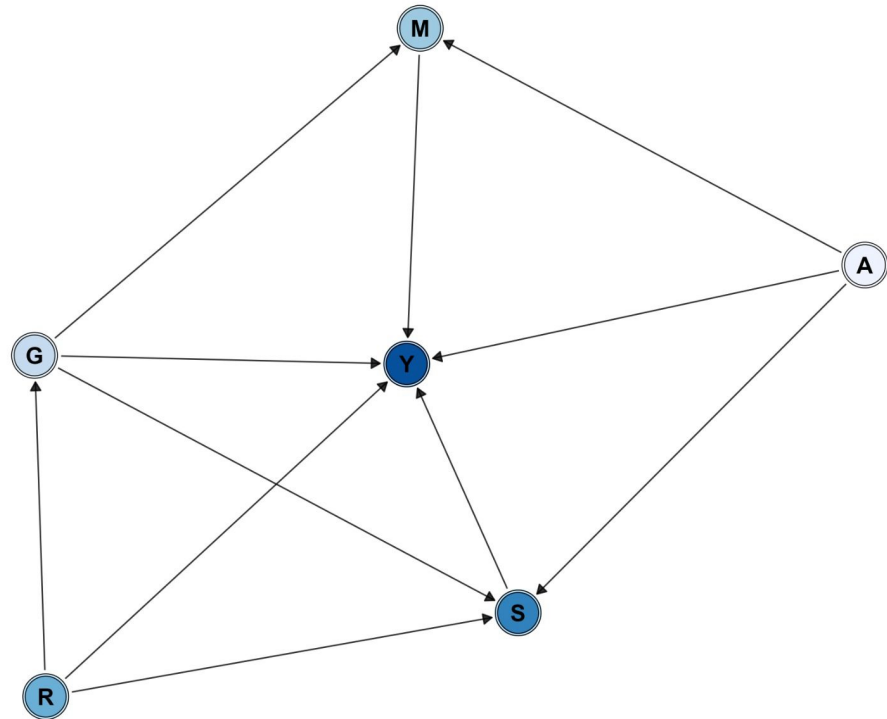
The effect of schooling on wages is endogenous, as can be seen in the DAG. However, using Double Machine Learning (DML) we are able to overcome this problem. Thus, it is possible to find out whether there is a causal effect of schooling on wages.

Moreover, this study is the first to address the Turkish education reform of 2012 –as well as education reforms in general– using an innovative method such as DML.

# DAG

DAG for Earnings Analysis

Y: Log hourly earnings  
R: Region  
G: Gender  
A: Age  
M: Marital Status  
S: Schooling

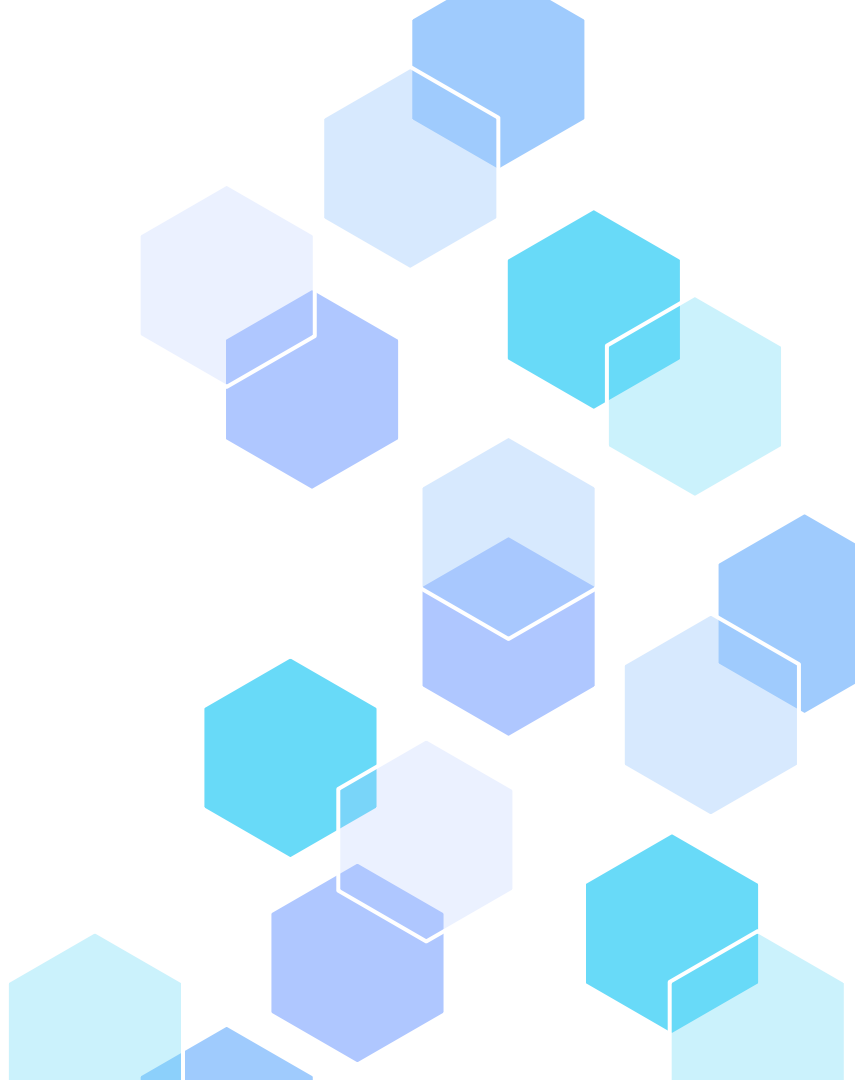


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# 02

# Methods

Step taken







# DATA CLEANING & FEATURE ENGINEERING

## DATA CLEANING



- *COMBINED THE DATASETS {2021,2022}*
- *RENAMED OUR VARIABLES*

## FEATURE ENGINEERING

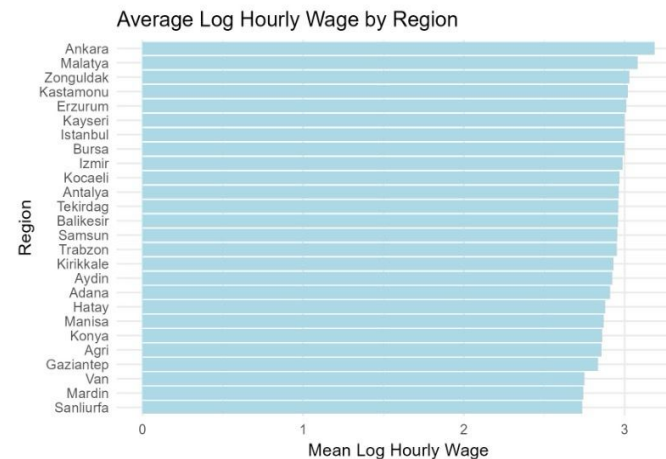
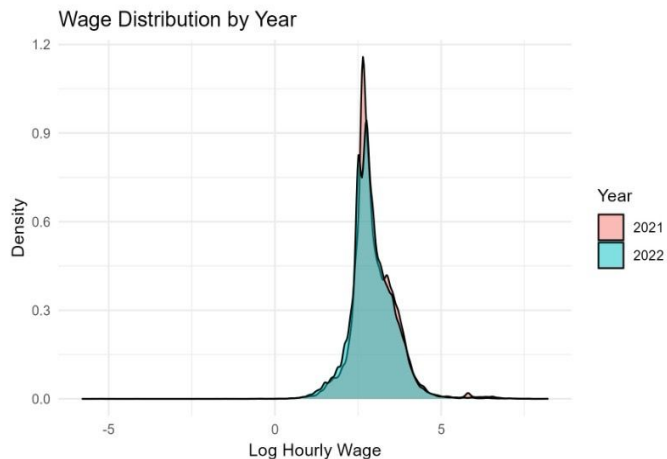
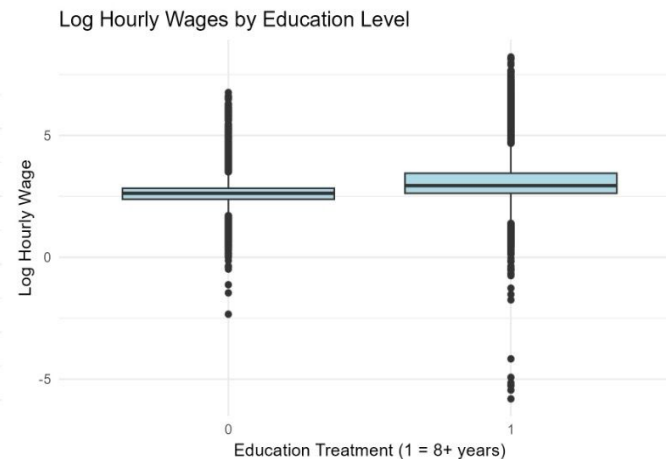
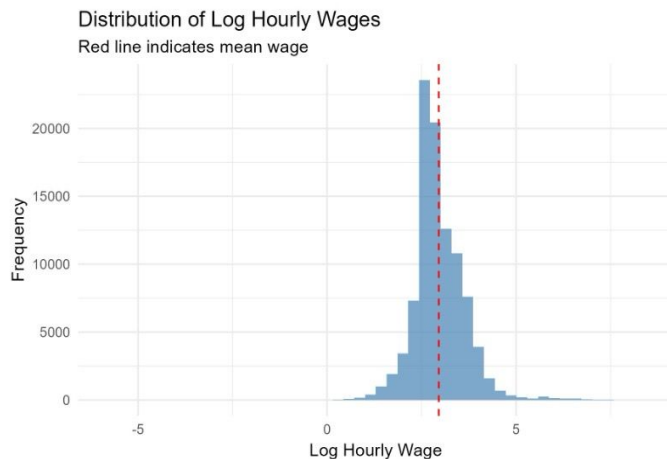
- *ENCODING CATEGORICAL VARIABLES(MARITAL STATUS, REGION)*
  - *NON-LINEAR CONTINUOUS VARIABLES (AGE, AGE-SQUARED)*
  - *CREATING LOG-HOURLY WAGE OUTCOME VARIABLES*
  - *CREATING TREATMENT VARIABLES FOR COMPULSORY SCHOOLING*
- 
- 



# EXPLORATORY DATA ANALYSIS



- *FILTER NA'S AND INTERMEDIATE VARIABLES*
  - *CHECK IF MISSING VALUES ARE MORE COMMON IN CERTAIN GROUPS*
  - *CREATE PLOTS TO VISUALIZE THE ASPECTS OF THE DATA*
- 
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# VISUALIZATION OF THE ASPECTS OF THE DATA



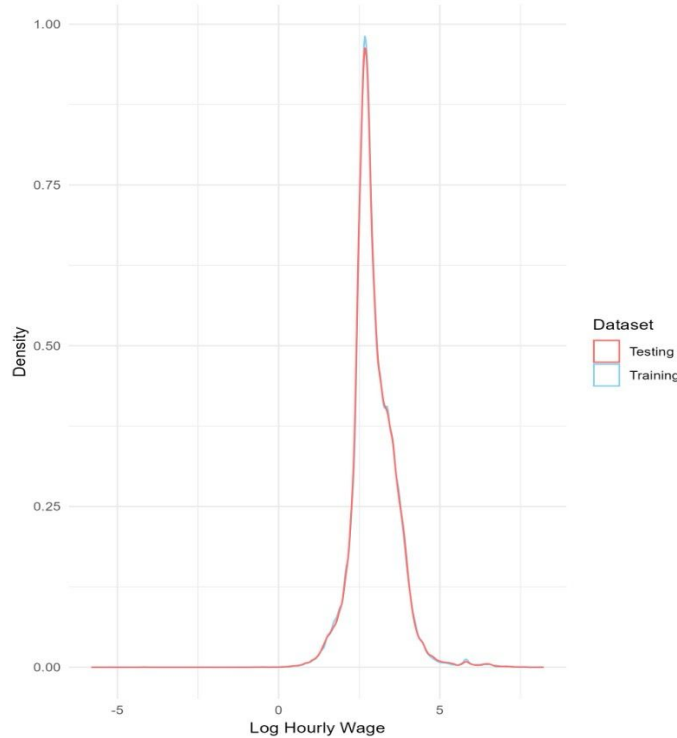


# MACHINE LEARNING MODELS

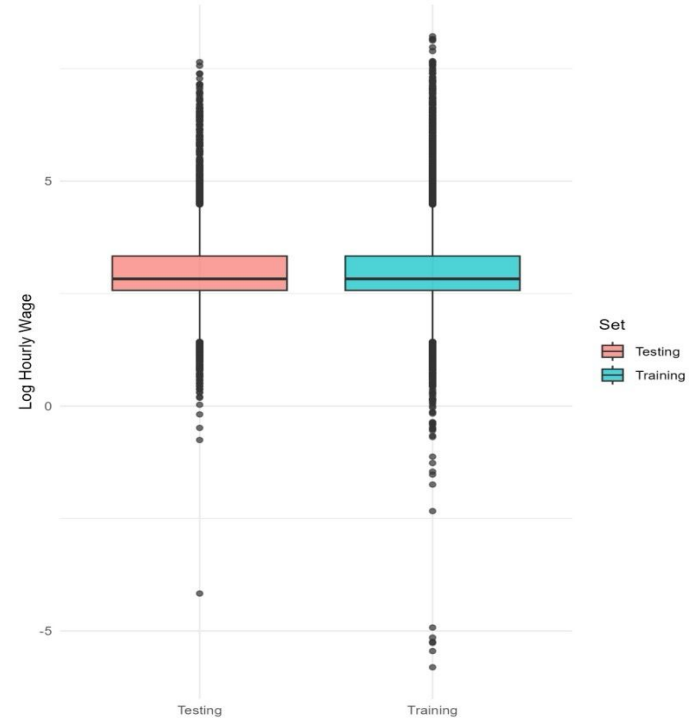
- *CHECK THE BALANCE OF THE DISTRIBUTION OF THE DATA*
  - *REGRESSION MODEL*
  - *DOUBLE MACHINE LEARNING*
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# BALANCE OF DATA SPLITS

Distribution of Log Hourly Wages  
Comparing Training and Testing Sets



Log Hourly Wages by Dataset  
Box Plot Comparison





# REGRESSION MODEL

$$\log\_hourly\_wage = \beta_0 + \beta_1 age + \beta_2 age^2 + \beta_3 marital\_status + \beta_4 region + \beta_5 gender + \beta_6 working\_hours + \beta_7 highschool\_completion$$

# DOUBLE MACHINE LEARNING

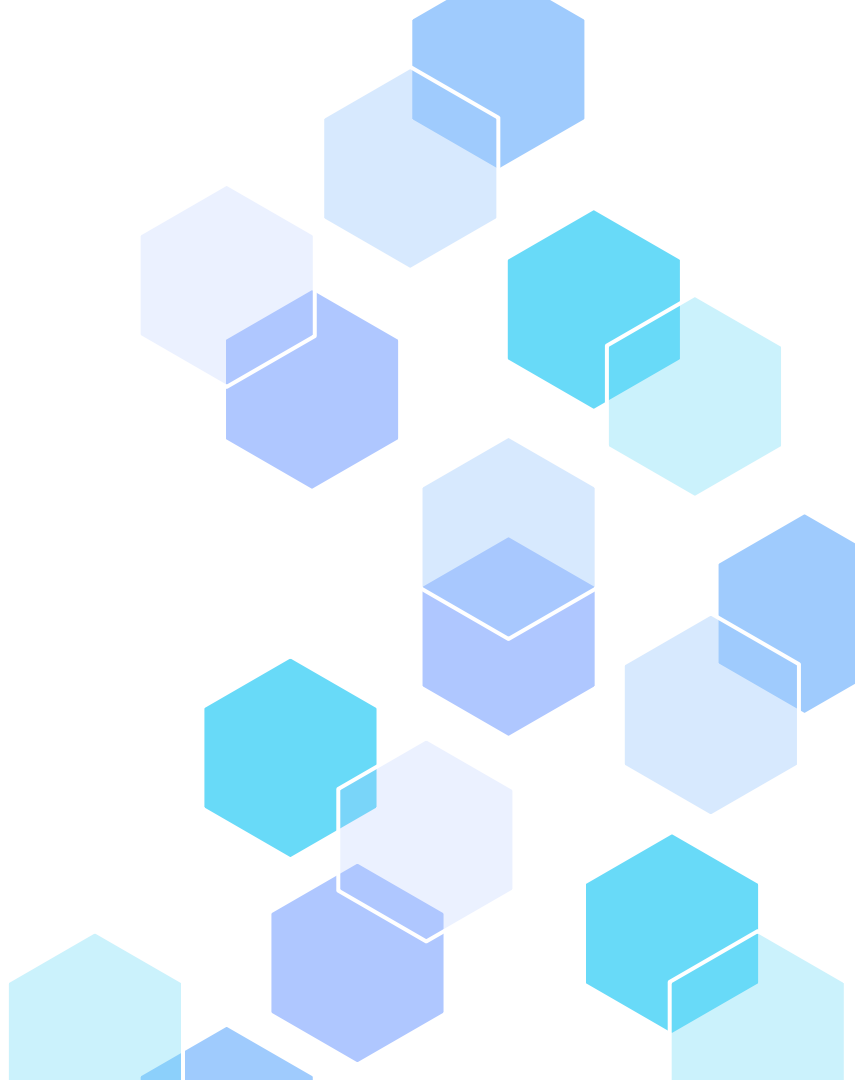
- Prepare data for DML
- Outcome variable (Y): log\_hourly\_wage,
- Treatment variable (D): Highschool education,
- Control variables (X): age, age\_sq, gender, marital\_status, region, working\_hours
- Create Double ML data object
- Create learners for both stages
- For predicting High-school education (classification task)
- For predicting wages (regression task)
- Create and fit DML model
- Fit the model

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# 03

# Results

Outcomes and Limitations

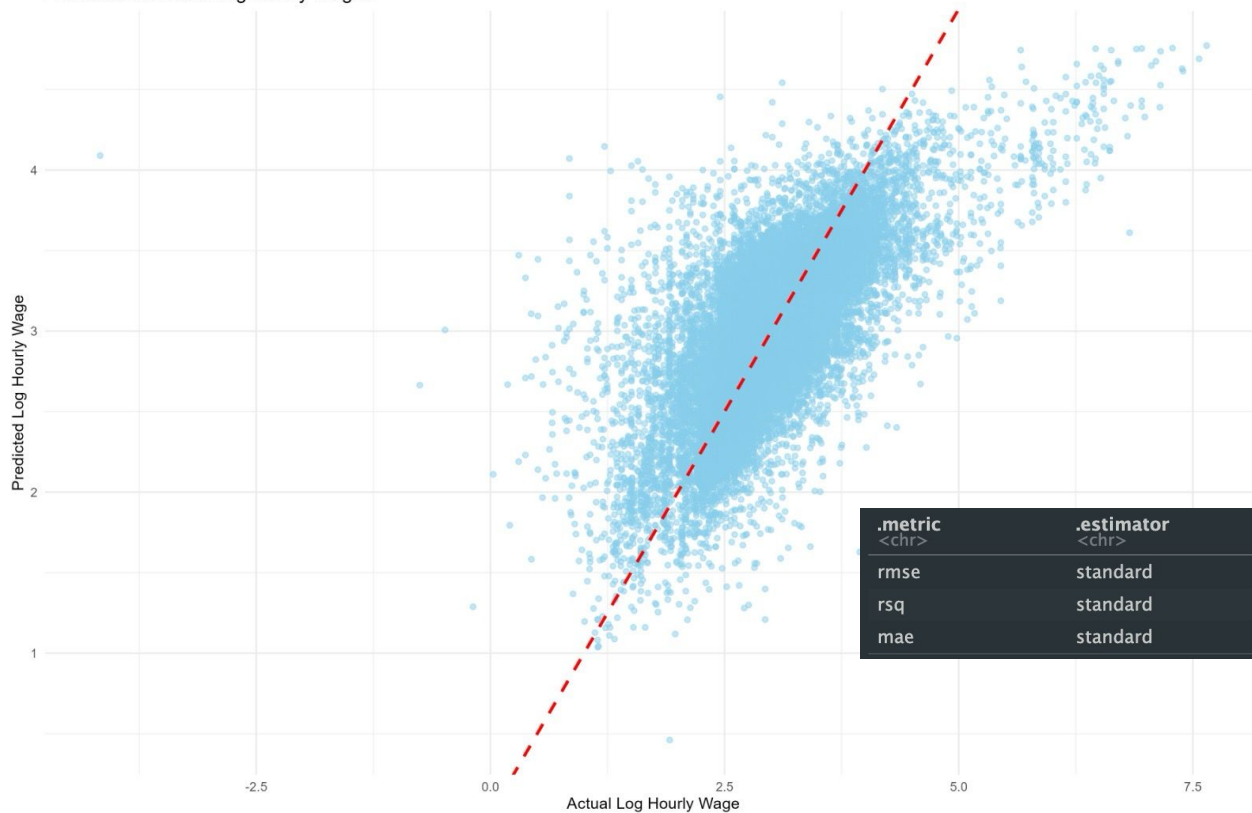


# REGRESSION MODEL

term <chr>	estimate <dbl>	std.error <dbl>	statistic <dbl>	p.value <dbl>
(Intercept)	2.68271750	0.003142203	853.76957	0.000000e+00
age	0.61094475	0.014177513	43.09252	0.000000e+00
age_sq	-0.54032359	0.013586607	-39.76884	0.000000e+00
treatment2	0.43566841	0.004074671	106.92112	0.000000e+00
working_hours	-0.35597757	0.001917370	-185.65932	0.000000e+00
gender_male	-0.08450761	0.001910236	-44.23935	0.000000e+00
marital_status_Ma...	0.03672317	0.002668978	13.75926	5.074654e-43
region_Manisa	-0.03546040	0.002193526	-16.16594	1.110789e-58
region_Adana	-0.03265749	0.002156648	-15.14271	1.015723e-51
region_Hatay	-0.02934735	0.002129216	-13.78317	3.647950e-43

# PREDICTED VS ACTUAL

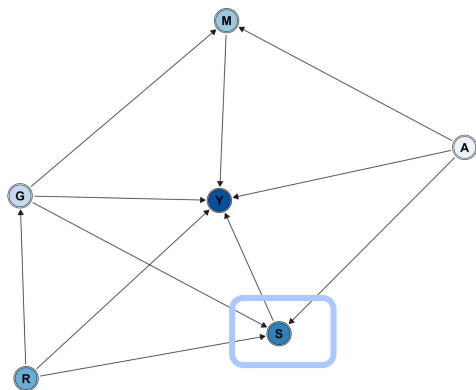
Predicted vs Actual Log Hourly Wages



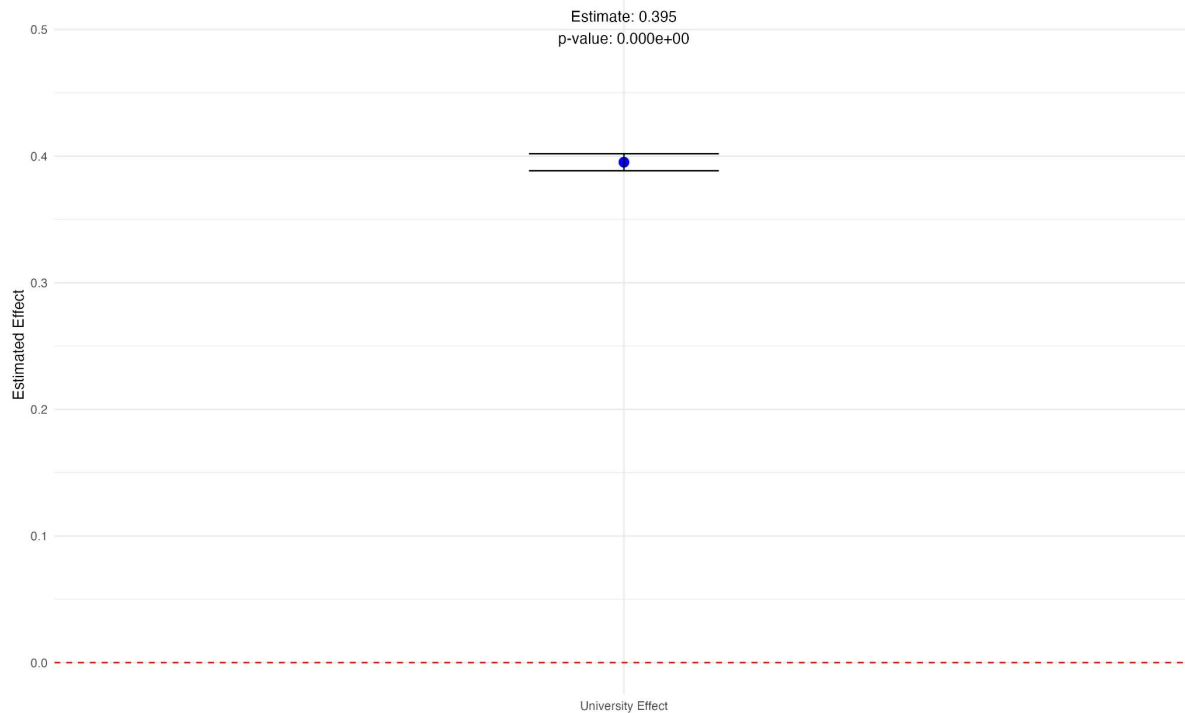
<code>.metric</code> <chr>	<code>.estimator</code> <chr>	<code>.estimate</code> <dbl>
rmse	standard	0.4917730
rsq	standard	0.4651916
mae	standard	0.3499310

# DOUBLE MACHINE LEARNING

DAG for Earnings Analysis



Effect of University Education on Log Hourly Wages  
Estimated using Double Machine Learning



# Interpretation of Results

## 1. Comparing the estimates of Linear Regression and DML

- LinReg estimated that completing highschool increases wages by 43% compared to people who did not.
- DML estimated that same treatment has 39% effect on wages.

## 2. Statistical significance

- From  $\sim 0$  p-values we can argue that they are statistically significant

## 3. Causal Inference

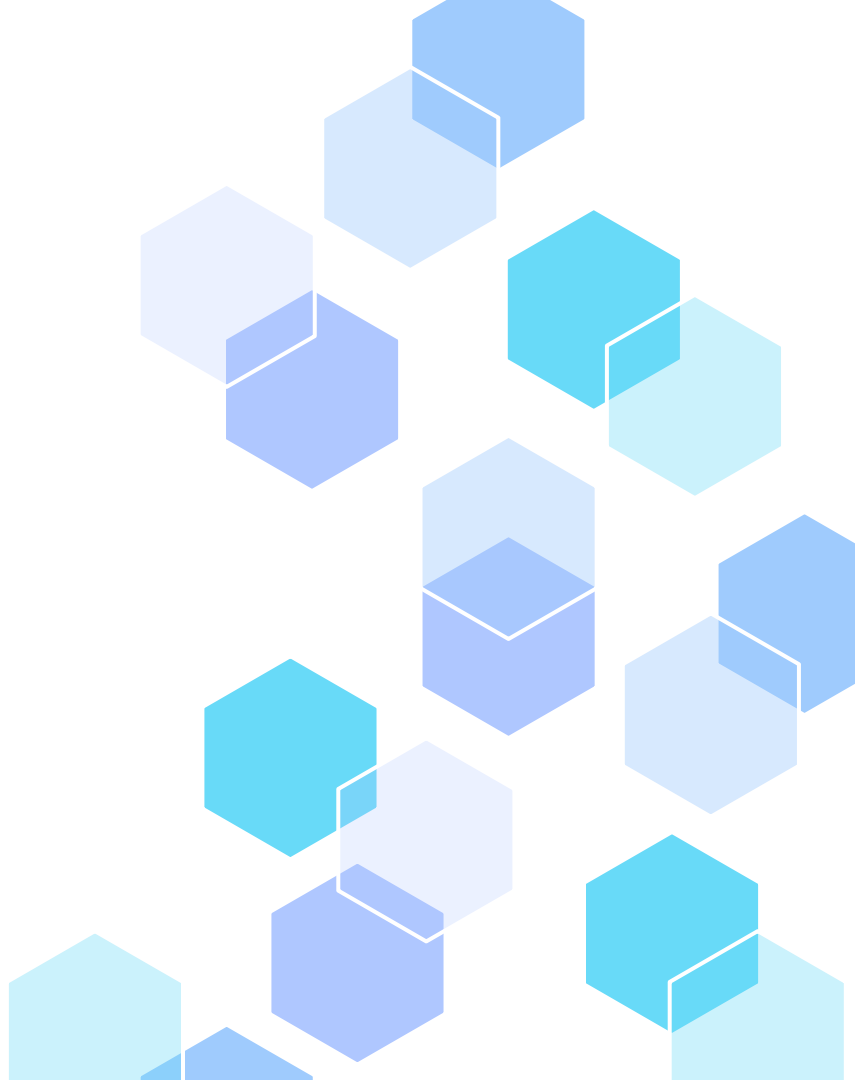
- DML removes the confounding effects on treatment variable hence its estimates can be used for causal arguments

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04

# CONCLUSION

INTERPRETATION OF RESULTS







Research Question: Was “4+4+4” policy effective?

Baseline Model Linear Regression showed promising results with ~50% accuracy (RMSE) and it predicted completing highschool increased wages by 43%

Using the DAG we argued that there would be endogenous variation in our treatment variable (highschool completion, specifically gender and region)

Then we used a state-of-the-art Double Machine Learning Technique for eliminating this endogenous variation.

Our DML model predicted that highschool completion increases wages by 39% – 4% less than baseline prediction.

We argue that this 4% was the overestimation of baseline model coming from endogenous variation.

Hence we argue that real effect of highschool completion is 39%, statistically significant and notably large.



Hence we conclude that policy change was a effective.

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# Thank you!

