The Effects of Graphics on Reading Comprehension of Causal Analytics Reports

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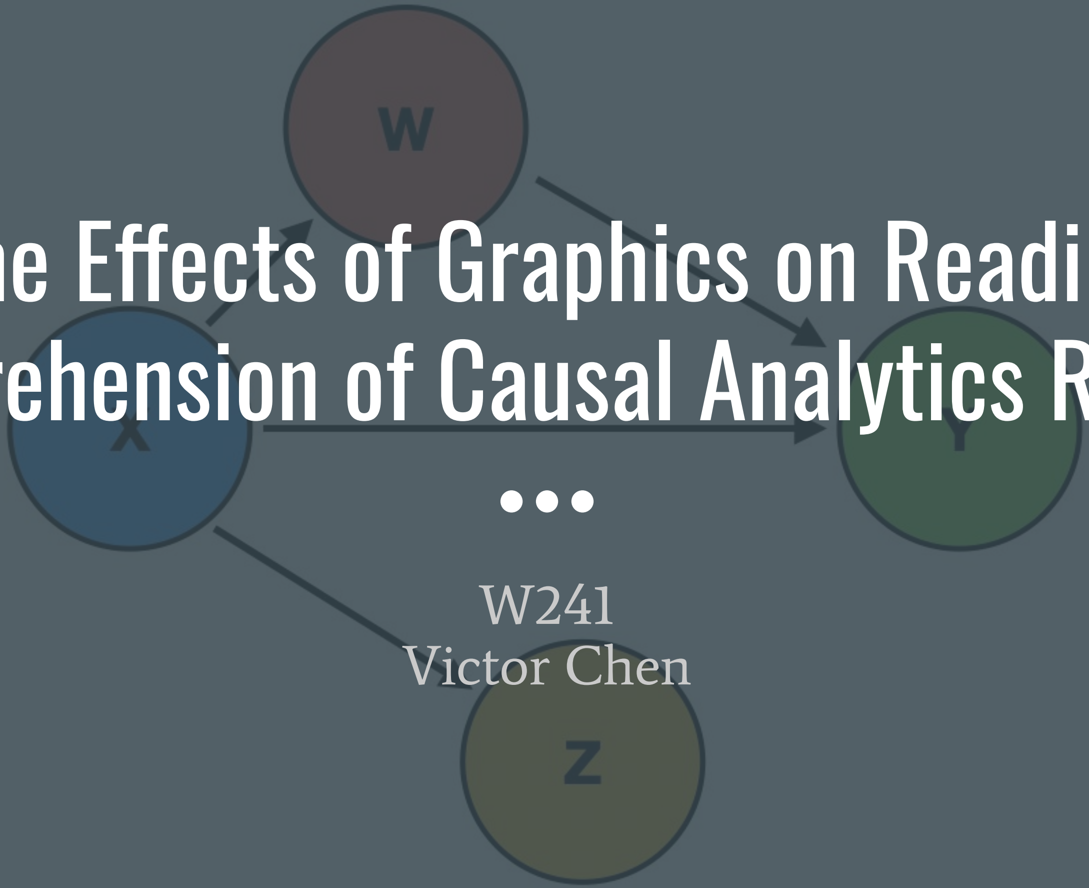
W241

Victor Chen



Background

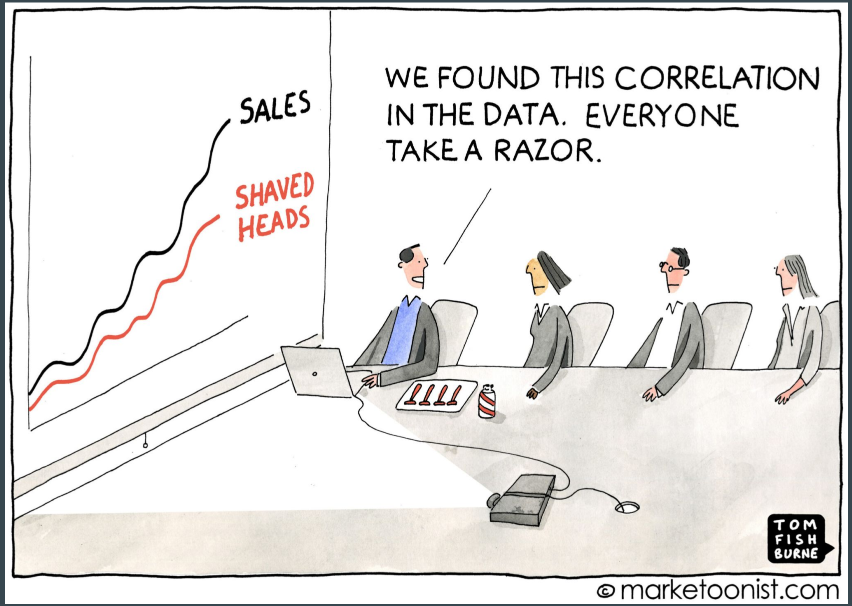
Pressed-for-time, story-focused executives

Data-savvy analysts

Background

Data analytics

Prescriptive analytics



Hypotheses

A graphic/visual representation of causal knowledge will lead to more effective translation of data insights into actionable prescriptions

- More accurate reading comprehension of complex analytics reports
- Higher confidence in the results
- Greater actionability of recommendations

Example

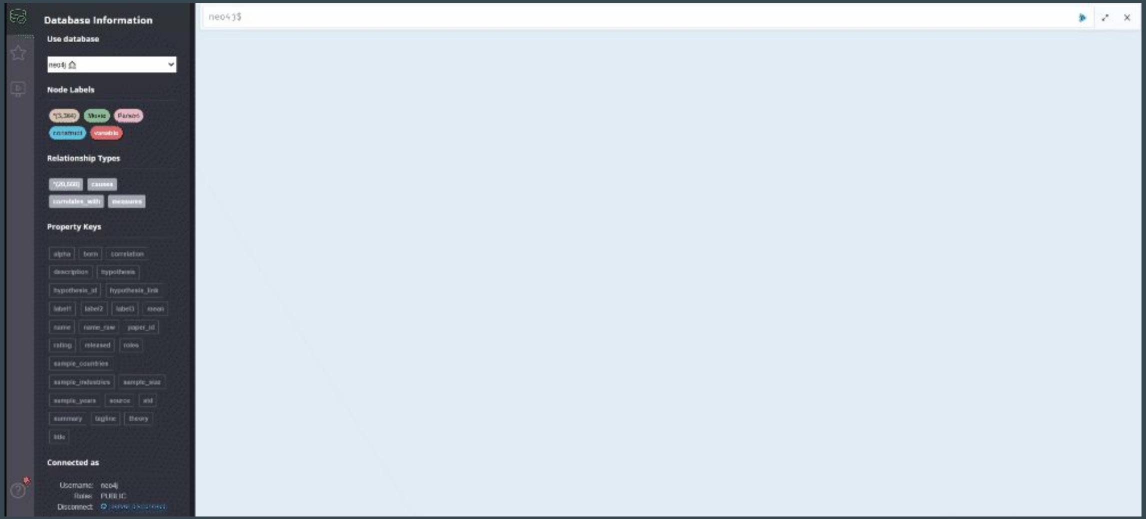
Data analytics

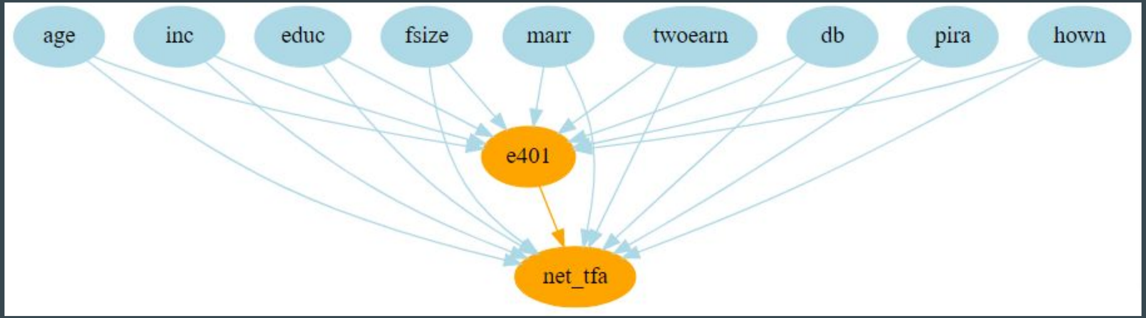
Prescriptive analytics

Example

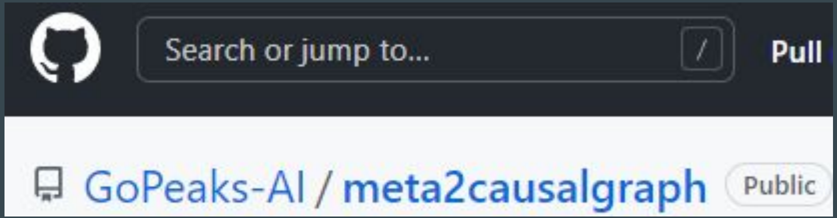
Data analytics

Prescriptive analytics





Example

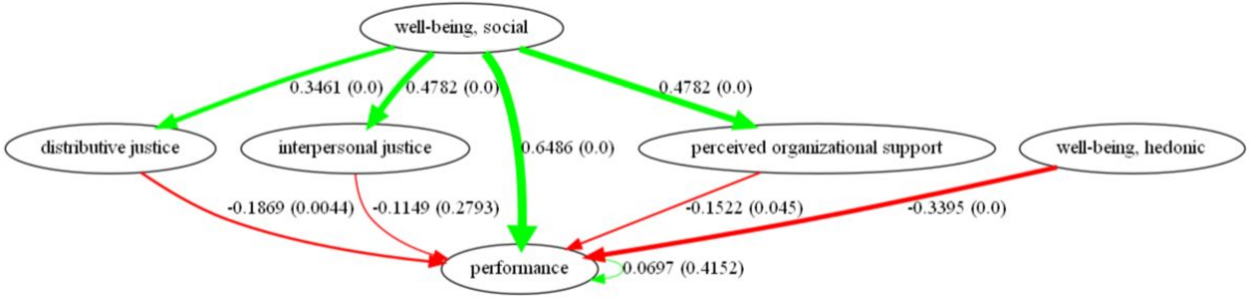


Data analytics

Prescriptive analytics

```
causal_graph(n1_level='label1',
             n2_level='label1',
             n1_searchterm='well-being',
             n2_searchterm='performance',
             search_method='contain',
             draw_graph=True
            )
```

```
Query has returned 5 findings on the direct causal link between 'well-being' and 'performance'.
Query has returned 3 findings on mediation between 'well-being' and 'performance'.
Query has returned 16 findings on the confounder between 'well-being' and 'performance'.
Query has returned 0 findings on the collider between 'well-being' and 'performance'.
```




```
Notes:
[1] link label shows the mean effect size (p-value in the parenthesis);
[2] link arrow shows the direction of causality;
[3] link color suggests the sign of the effect size: green for positive, and red for negative;
[4] link thickness suggests the magnitude of the effect size.
```

Hypothesis

A graphic/visual representation of causal knowledge will lead to a more accurate reading comprehension of analytics reports.

Control

Berkeley
UNIVERSITY OF CALIFORNIA

Does 401(k) Eligibility affect Financial Wealth?

A recent study on the effects of 401(k) eligibility on financial wealth was published in American Economic Review in 2017. This study examined a sample of households from wave 4 of the 1990 U.S. Survey of Income and Program Participation (SIPP), where the observations are limited to households in which the reference person is 25-64 years old, at least one person is employed, and no one is self-employed. The sample consists of 9915 households, and all dollar amounts are in 1991 dollars. The sample shows a $19,559 mean difference between households ineligible for 401(k) and those eligible for 401(k). That is, on average, households eligible for 401(k) had almost $20,000 more in net financial assets than those ineligible for 401(k). But this simple mean difference has not controlled for covariates like age, income, family size, marriage status, two-earner status, defined benefit (DB) pension status, IRA participation status, and homeownership status. Because these covariates may directly affect a household's 401(k) eligibility, the study further used machine learning techniques to reduce the confounding biases from the data. After debiasing the data, there is an approximately $8000 - $9000 effect of the debiased measure of 401(k) eligibility on the debiased measure of a household's net financial assets. Additionally, a linear regression estimated a coefficient of $5896 of 401(k) eligibility on a household's net financial assets, after controlling for all the covariates, suggesting that everything being equal, a household eligible for 401(k) on average tends to earn almost $6000 more in net financial assets. These findings suggest a clear positive relationship between 401(k) eligibility and a household's financial wealth. But the exact estimates vary depending on the research methods.

Based on this study, how many additional 1991 dollars in a household's net financial assets would be caused by 401(k) eligibility, everything else being equal?

References

[1] Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., & Newey, W. (2017). Double/debiased/Neyman machine learning of treatment effects. *American Economic Review, 107*(5), 261-65.
[2] DoubleML (2021). Python: Impact of 401(k) on financial wealth. Accessible at https://docs.doubleml.org/stable/examples/py_double_ml_pension.html.

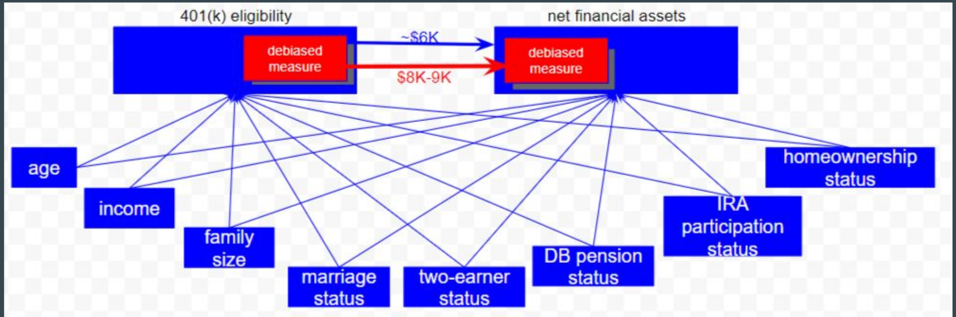
- $19,559
- $8000-$9000
- Almost $6000

Treatment

Berkeley
UNIVERSITY OF CALIFORNIA

Does 401(k) Eligibility affect Financial Wealth?

A recent study on the effects of 401(k) eligibility on financial wealth was published in American Economic Review in 2017. This study examined a sample of households from wave 4 of the 1990 U.S. Survey of Income and Program Participation (SIPP), where the observations are limited to households in which the reference person is 25-64 years old, at least one person is employed, and no one is self-employed. The sample consists of 9915 households, and all dollar amounts are in 1991 dollars. The sample shows a $19,559 mean difference between households ineligible for 401(k) and those eligible for 401(k). That is, on average, households eligible for 401(k) had almost $20,000 more in net financial assets than those ineligible for 401(k). But this simple mean difference has not controlled for covariates like age, income, family size, marriage status, two-earner status, defined benefit (DB) pension status, IRA participation status, and homeownership status. Because these covariates may directly affect a household's 401(k) eligibility, the study further used machine learning techniques to reduce the confounding biases from the data. After debiasing the data, there is an approximately $8000 - $9000 effect of the debiased measure of 401(k) eligibility on the debiased measure of a household's net financial assets. Additionally, a linear regression estimated a coefficient of $5896 of 401(k) eligibility on a household's net financial assets, after controlling for all the covariates, suggesting that everything being equal, a household eligible for 401(k) on average tends to earn almost $6000 more in net financial assets. These findings suggest a clear positive relationship between 401(k) eligibility and a household's financial wealth. But the exact estimates vary depending on the research methods.



Based on this study, how many additional 1991 dollars in a household's net financial assets would be caused by 401(k) eligibility, everything else being equal?

References

[1] Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., & Newey, W. (2017). Double/debiased/Neyman machine learning of treatment effects. *American Economic Review, 107*(5), 261-65.
[2] DoubleML (2021). Python: Impact of 401(k) on financial wealth. Accessible at https://docs.doubleml.org/stable/examples/py_double_ml_pension.html.

- $19,559
- $8000-$9000
- Almost $6000

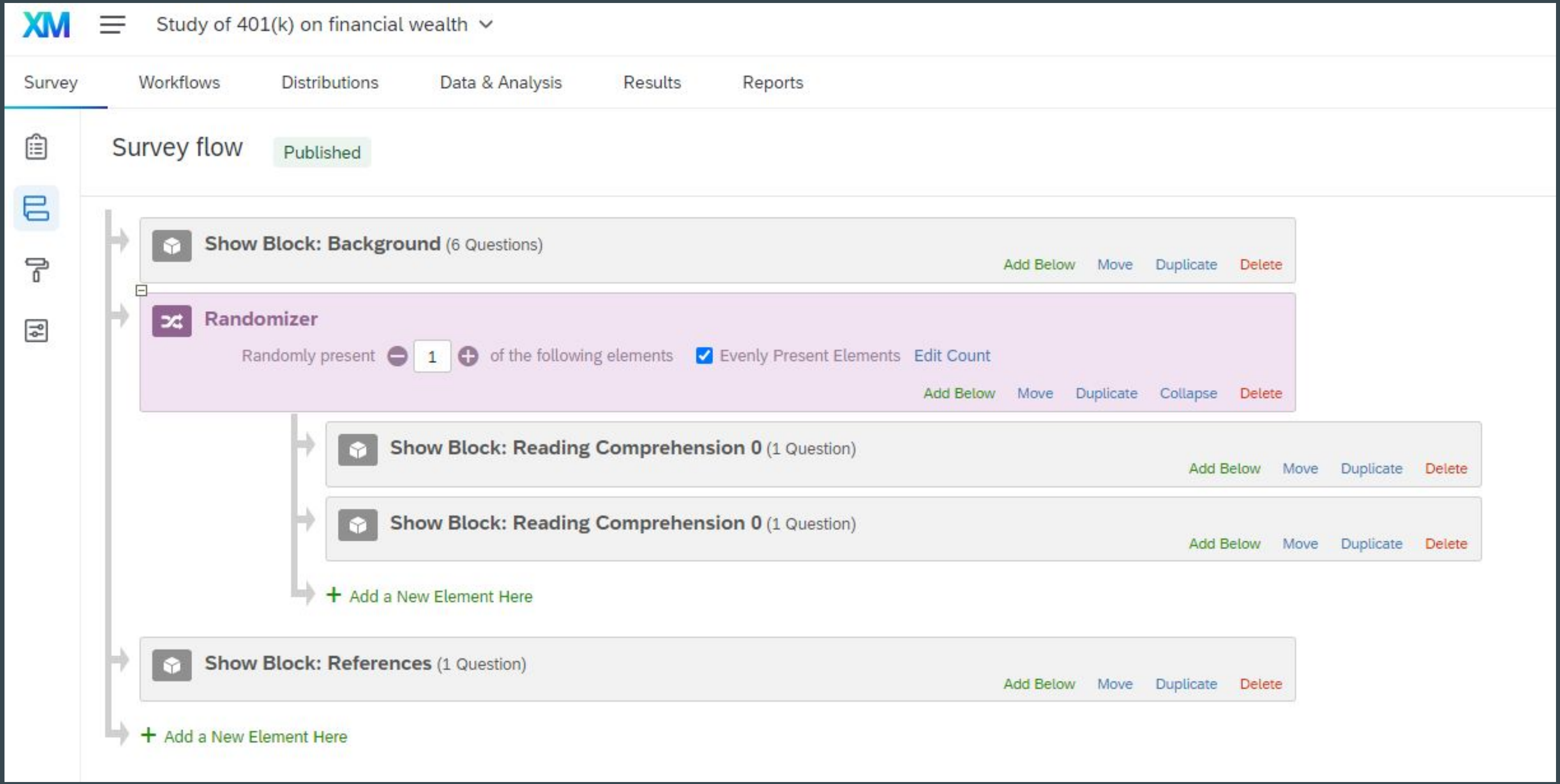
Measurement Unit

Unique individual Amazon M-Turks workers whose first language is EN, and are living in the United States

URL

Unique survey code

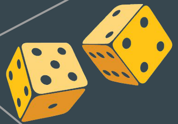
Randomization



Workflow and Causation

MTurks responses
N = 154

Completed/ verified responses on Qualtrics
N = 147



Control group
N = 75

Treatment group
N = 72

Outcome measures

Main Y:

- Correct answer (1 correct, 0 wrong) on the expected effects of enrollment in 401k on net financial assets in 1991 dollars, on average

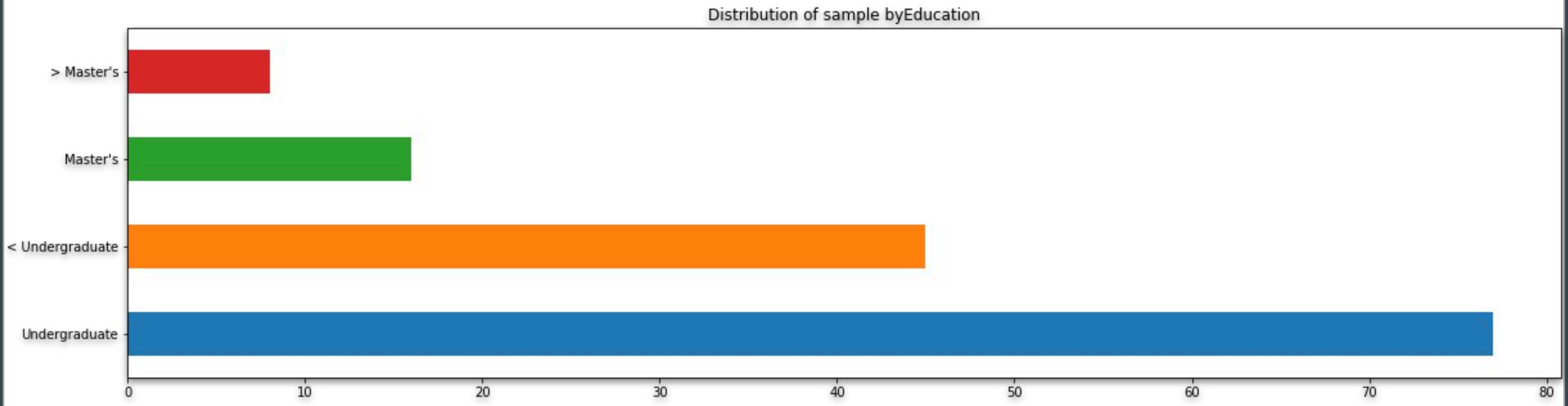
Secondary Ys:

- Reading speed (in seconds)
- Whether to check external sources (1 yes, 0 no)

Control group
N = 75

Treatment group
N = 72

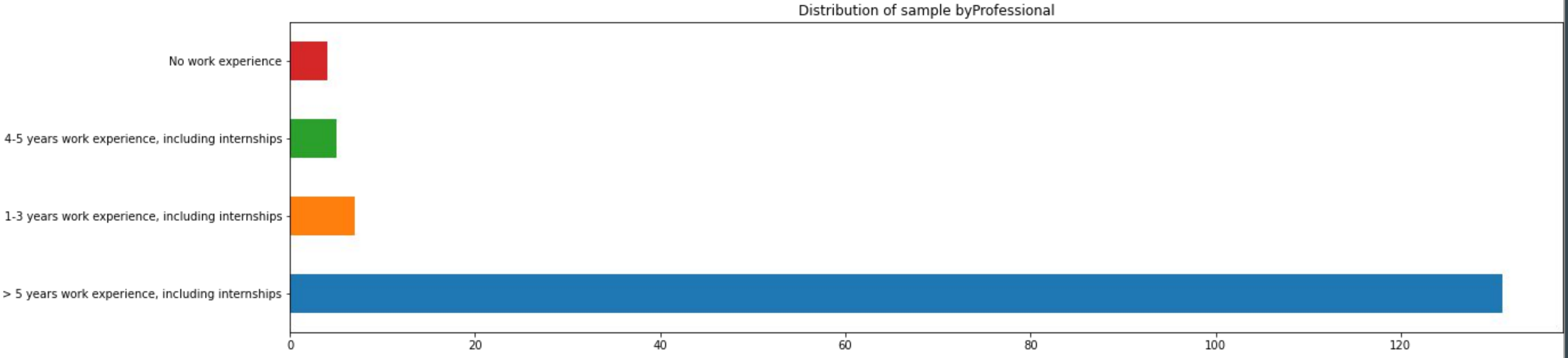
Data Analysis - Summary



Data Analysis - Summary

```
Group      Education
Control    Undergraduate       37
           < Undergraduate     29
           Master's             7
           > Master's           1
Treatment  Undergraduate       40
           < Undergraduate     16
           Master's             9
           > Master's           7
Name: Education, dtype: int64
Difference in education score: 0.11555555555555554
The variances are 0.09528888888888885 and 0.17283950617283966 for the control and treatment groups, respectively.
The t-test of the mean education difference has a p-value of 0.058709107659612805.
```

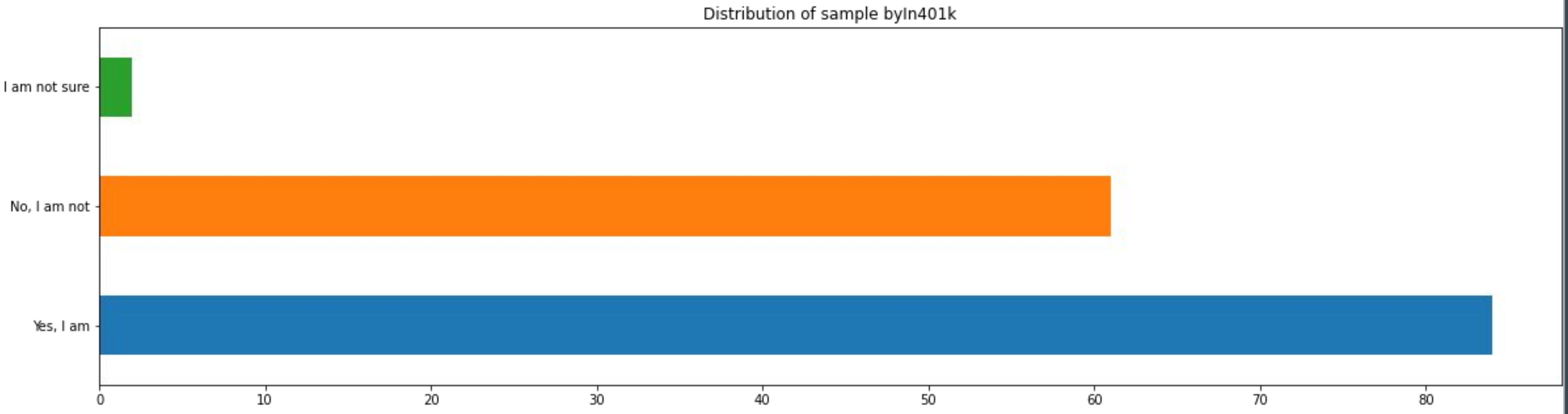
Data Analysis - Summary (cont'd)



Data Analysis - Summary (cont'd)

```
Group      Professional
Control    > 5 years work experience, including internships    67
           No work experience                                    4
           1-3 years work experience, including internships     3
           4-5 years work experience, including internships     1
Treatment  > 5 years work experience, including internships    64
           1-3 years work experience, including internships     4
           4-5 years work experience, including internships     4
Name: Professional, dtype: int64
Difference in experience score: 0.08666666666666689
The variances are 0.5891555555555563 and 0.2500000000000001 for the control and treatment groups, respectively.
The t-test of the mean experience score difference has a p-value of 0.4238107594329512.
```

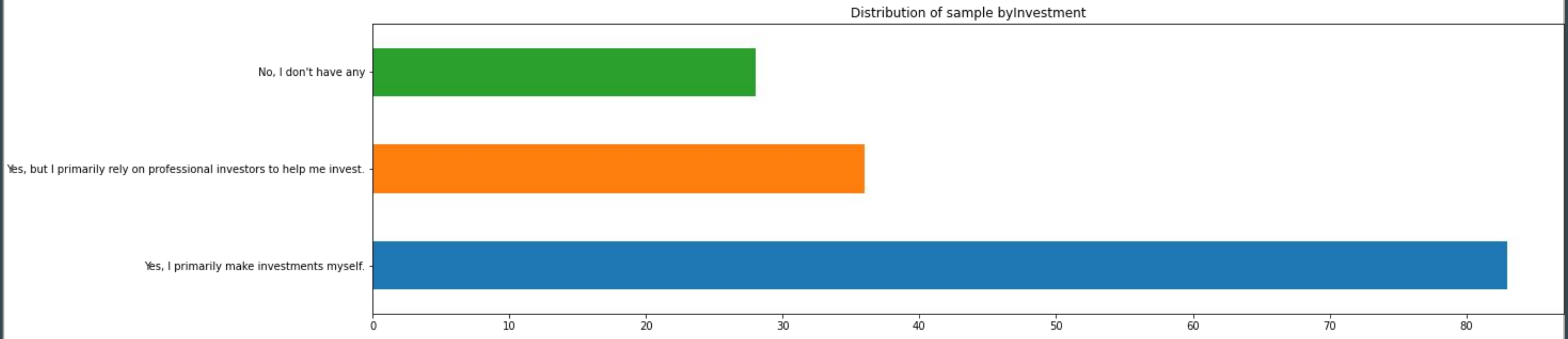
Data Analysis - Summary (cont'd)



Data Analysis - Summary (cont'd)

```
Group      In401k
Control    Yes, I am         39
           No, I am not      36
Treatment  Yes, I am         45
           No, I am not      25
           I am not sure      2
Name: In401k, dtype: int64
Difference in 401k status: 0.10499999999999998
The variances are 0.2496 and 0.234375 for the control and treatment groups, respectively.
The t-test of the mean 401k status difference has a p-value of 0.20103306368696297.
```

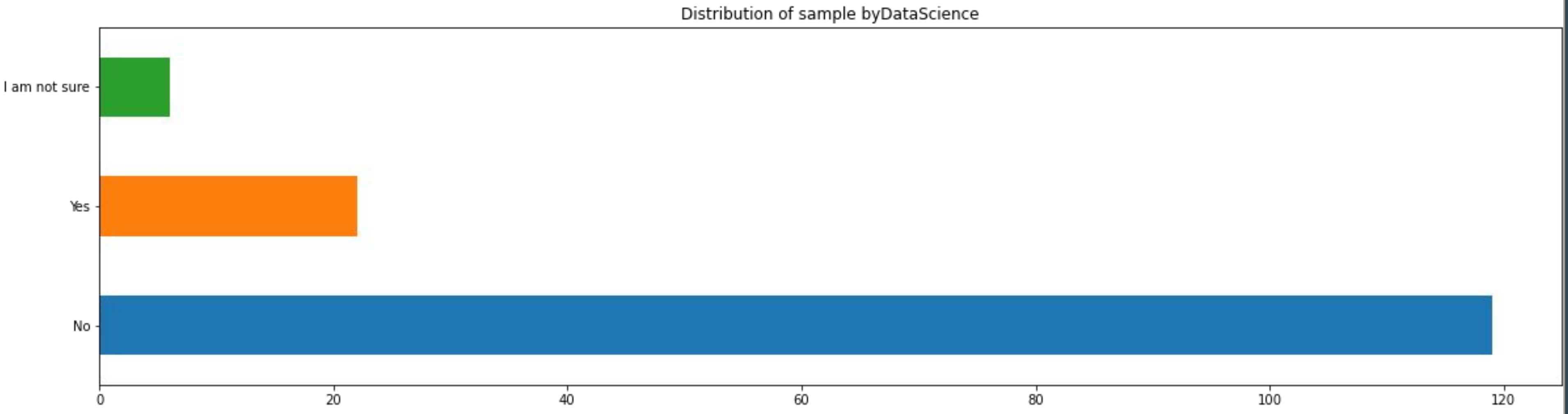
Data Analysis - Summary (cont'd)



Data Analysis - Summary (cont'd)

```
Group      Investment
Control    Yes, I primarily make investments myself.                                  39
           No, I don't have any                                                       19
           Yes, but I primarily rely on professional investors to help me invest.     17
Treatment  Yes, I primarily make investments myself.                                  44
           Yes, but I primarily rely on professional investors to help me invest.     19
           No, I don't have any                                                        9
Name: Investment, dtype: int64
Difference in investment background: 0.10972222222222228
The variances are 0.17555555555555546 and 0.12495177469135793 for the control and treatment groups, respectively.
The t-test of the mean difference in investment background has a p-value of 0.09108924246338256.
```

Data Analysis - Summary (cont'd)



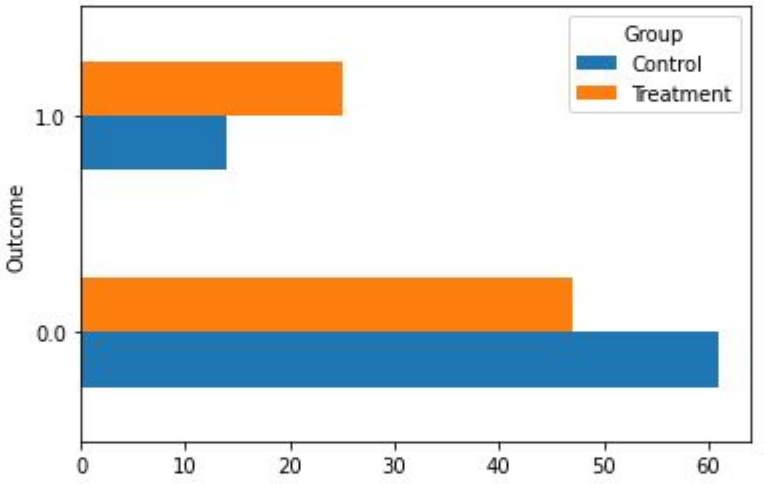
Data Analysis - Summary (cont'd)

```
Group      DataScience
Control    No                 62
           Yes                10
           I am not sure       3
Treatment  No                 57
           Yes                12
           I am not sure       3
Name: DataScience, dtype: int64
Difference in Data science background: 0.033333333333333326
The variances are 0.11555555555555558 and 0.13888888888888895 for the control and treatment groups, respectively.
The t-test of the mean difference in Data science background has a p-value of 0.5742522857891523.
```

Data Analysis - Correctness of the answer

```
Control group answers:
Almost $6000    41
$19,559         20
$8000-$9000     14
Name: Control, dtype: int64

Treatment group answers:
Almost $6000    32
$8000-$9000     25
$19,559         15
Name: Treatment, dtype: int64
```

```
--------------------------------------------------
Distribution of outcome by group
--------------------------------------------------

<AxesSubplot:ylabel='Outcome'>
```



Data Analysis - Correctness of the answer (Cont'd)

```python
print("-" * 50)
print("Mean outcoem by group")
print("-" * 50)
print(df.groupby('Group')['Outcome'].mean())
```

```
--------------------------------------------------
Mean outcoem by group
--------------------------------------------------
Group
Control      0.1867
Treatment    0.3472
Name: Outcome, dtype: float64
```

```python
Y1 = df[df['Group']=='Treatment']['Outcome']
Y0 = df[df['Group']=='Control']['Outcome']
print("ATE:", Y1.mean() - Y0.mean())
print("The variances are {} and {} for the control and treatment groups, respectively.".format(np.var(Y0), np.var(Y1)))
print("The t-test of the mean outcome difference has a p-value of {}.".format(stats.ttest_ind(Y1, Y0, equal_var=True)[1]))
```

```
ATE: 0.16055555555555553
The variances are 0.151822222222222 and 0.22665895061728392 for the control and treatment groups, respectively.
The t-test of the mean outcome difference has a p-value of 0.027544900175178758.
```

Data Analysis - Correctness of the answer (Cont'd)

Logit Regression Results

Dep. Variable:	Outcome	No. Observations:	147
Model:	Logit	Df Residuals:	140
Method:	MLE	Df Model:	6
Date:	Tue, 12 Apr 2022	Pseudo R-squ.:	0.04912
Time:	23:44:23	Log-Likelihood:	-80.867
converged:	True	LL-Null:	-85.045
Covariance Type:	HC3	LLR p-value:	0.2133

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-1.4978	0.766	-1.955	0.051	-2.999	0.004
C(Group)[T.Treatment]	0.8923	0.400	2.231	0.026	0.109	1.676
education_score	-0.3790	0.421	-0.901	0.367	-1.203	0.445
experience_score	0.0663	0.630	0.105	0.916	-1.169	1.302
e401k_status	0.2912	0.411	0.708	0.479	-0.515	1.098
investment_background	-0.1354	0.519	-0.261	0.794	-1.152	0.881
data_science_background	0.6818	0.522	1.307	0.191	-0.341	1.704

Data Analysis - Subsample test 1: Education

0 for < UG

1 for UG +

```
1    101
0     46
Name: education_score, dtype: int64

education score: 0
ATE: 0.14166666666666666
The variances are 0.17888888888888888 and 0.234375 for the control and treatment groups, respectively.
The t-test of the mean outcome difference has a p-value of 0.320224947478l813.

education score: 1
ATE: 0.18373015873015874
The variances are 0.13135802469135 81 and 0.2241709183673471 for the control and treatment groups, respectively.
The t-test of the mean outcome difference has a p-value of 0.03607277577286542.
```

Data Analysis - Subsample test 2: Work experience

0 for < = 5 years work experience

1 for 5+ years work experience

```
1    131
0     16
Name: experience_score, dtype: int64

Work experience score: 1
ATE: 0.19519589552238806
The variances are 0.1372243261305412 and 0.230224609375 for the control and treatment groups, respectively.
The t-test of the mean outcome difference has a p-value of 0.010613096924951873.

Work experience score: 0
ATE: -0.125
The variances are 0.234375 and 0.1875 for the control and treatment groups, respectively.
The t-test of the mean outcome difference has a p-value of 0.6185599512335765.
```

Data Analysis - Subsample test 3: 401k status

Yes, I'm currently enrolled in 401k

No, I'm not

```
Yes, I am        84
No, I am not     63
Name: In401k, dtype: int64

Enrolled in 401k: No, I am not
ATE: 0.12962962962962962
The variances are 0.13888888888888887 and 0.20850480109739364 for the control and treatment groups, respectively.
The t-test of the mean outcome difference has a p-value of 0.22725246004317023.

Enrolled in 401k: Yes, I am
ATE: 0.17264957264957265
The variances are 0.1630506245890861 and 0.23506172839506173 for the control and treatment groups, respectively.
The t-test of the mean outcome difference has a p-value of 0.08624412598748671.
```

Data Analysis - Subsample test 4: Investment background

0 if not involved in personal investments

1 if involved in personal investments

```
1    83
0    64
Name: investment_background, dtype: int64

investment background: 1
ATE: 0.2097902097902098
The variances are 0.13017751479289943 and 0.23140495867768582 for the control and treatment groups, respectively.
The t-test of the mean outcome difference has a p-value of 0.030818486949751207.

investment background: 0
ATE: 0.09920634920634924
The variances are 0.17283950617283966 and 0.21811224489795905 for the control and treatment groups, respectively.
The t-test of the mean outcome difference has a p-value of 0.38070771208171583.
```

Data Analysis - Subsample test 5: Data science training

Yes, I did

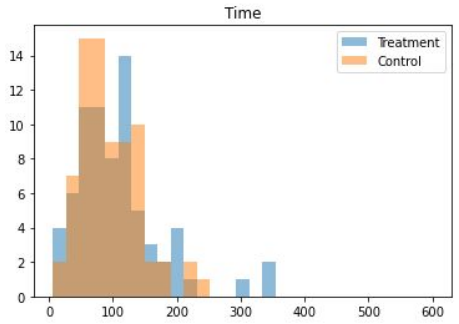
No, I did not

```
No     125
Yes     22
Name: DataScience, dtype: int64

Data science: No
ATE: 0.1474358974358974
The variances are 0.14059171597633133 and 0.2163888888888889 for the control and treatment groups, respectively.
The t-test of the mean outcome difference has a p-value of 0.05443764110466267.

Data science: Yes
ATE: 0.2
The variances are 0.21000000000000002 and 0.25 for the control and treatment groups, respectively.
The t-test of the mean outcome difference has a p-value of 0.3659958339806202.
```

Data Analysis - Other findings

Reading speed (time taken in seconds to complete the survey)

```
--------------------------------------------------
Histogram of Time (seconds)
--------------------------------------------------
```



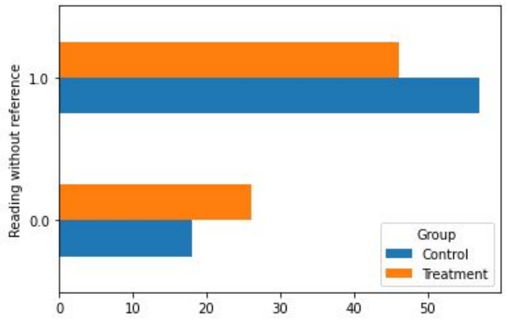

```
Y1 = df[df['Group']=='Treatment']['Time']
Y0 = df[df['Group']=='Control']['Time']

print("ATE:", Y1.mean() - Y0.mean())
print("The variances are {} and {} for the control and treatment groups, respectively.".format(np.var(Y0), np.var(Y1)))
print("The t-test of the mean time difference has a p-value of {}.".format(stats.ttest_ind(Y1, Y0, equal_var=True)[1]))
```

```
ATE: -0.3072222222222223
The variances are 16839.43395555556 and 4579.161844135802 for the control and treatment groups, respectively.
The t-test of the mean time difference has a p-value of 0.9858491683781828.
```

Data Analysis - Other findings

Checking external sources (1 yes, 0 no)

```
-------------------------------------------------
Distribution of Reading without reference by group
-------------------------------------------------

<AxesSubplot:ylabel='Reading without reference'>
```




```
Y1 = df[df['Group']=='Treatment']['Reading without reference']
Y0 = df[df['Group']=='Control']['Reading without reference']

print("ATE:", Y1.mean() - Y0.mean())
print("The variances are {} and {} for the control and treatment groups, respectively.".format(np.var(Y0), np.var(Y1)))
print("The t-test of the mean difference in Reading without reference has a p-value of {}.".format(stats.ttest_ind(Y1, Y0, eq
```

```
ATE: -0.12111111111111117
The variances are 0.1824000000000003 and 0.23070987654321 for the control and treatment groups, respectively.
The t-test of the mean difference in Reading without reference has a p-value of 0.11044704614405117.
```

Conclusion and Discussion

- Causal graph/visualization has
    - Increased the accuracy of reading comprehension
    - Without changes in the reading speed or whether or not to seek external sources
- Subsample tests are generally consistent, with some subsamples to small to have enough statistical power (e.g., p value).
- Results remain consistent after controlling for covariates in a regression model

Conclusion and Discussion

- If I had more budget and time, what would I have done differently?
  - Blocking and randomization within each block by key predictors: data science training, etc.
  - More examples in multiple disciplines and fields, from daily topics like healthcare to specialized topics such as neuroscience;
  - More varieties of the underlying analytics reports, e.g., DML to synthetic control, instrumental variables, etc.
  - Effects of causal graphs on the entire workflow between data science and decision-making

Q&As