Introduction to Causal Inference — 097400
Project Proposal

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1 Causal Question Articulation

In our project, we aim to answer a fundamental question in human sociology-

> Does the financial status of a person, compared to that of their country, **causally** affect their mental well-being?

This question is one that we believe is interesting, regardless of the results of our analysis. An ATE of 0 or a non-zero value is just as interesting.

In terms of causal effect analysis, or causal inference, our treatment variable is the relative financial status of a person. Although this value is self-related and not precisely calculated, we firmly believe that all SUTVA assumptions are met in this case.

The dataset we chose to work on, which we'll elaborate on in Section 3, is comprised of well-structured questions from a questionnaire completed by tens of thousands of European citizens in 2007 and 2011. The questions leave very little room for interpretation, and we take the answers as candid.

The outcome variable we chose may sound a little too abstract; however, we can examine a well-defined index, defined by the World Health Organization (WHO), called *WHO-5*. The index is designed to assess a person's mental status over the past 2 weeks, but its applications extend far beyond this short period. The index is measured by summing the answers to five questions, with possible answers ranging from 0 to 5, and then multiplying the result by 4 to achieve a score of 0-100. The WHO recommends referring patients with WHO-5 <50 for further assessment of depressive disorders (World Health Organization, 2022).

In the dataset, we have multiple covariates with diverse causal roles, including confounders, mediators, and effect modifiers. These covariates are responses to various questions regarding a person's education, employment, living conditions, overall life satisfaction, general health, and other factors.

Ultimately, the causal question we aim to answer is: What are the ATE (average treatment effect) for our treatment and outcome variables?

2 Existing Knowledge

A growing body of empirical literature has examined the relationship between financial status and mental well-being, laying a solid foundation for our proposed investigation. Existing studies have highlighted both correlational and mechanistic pathways through which economic standing—both absolute and relative—may impact psychological health.

One relevant line of research focuses on demographic and regional disparities in mental health outcomes. Kovacs et al. (2024) examined mental health determinants in socio-economically deprived areas of the European Union, finding significant age-related shifts in the predictors of psychological well-being. Their study emphasises the importance of subjective financial status and social context as drivers of mental health, although it does not attempt to establish causal effects directly.

Similarly, Hawkins, Mallapareddi, and Misra (2023) studied the association between social mobility and perinatal depression among Black women, underscoring the role of perceived economic trajectory rather than static income levels. Their findings highlight the psychological costs of downward mobility and the potential mental health benefits of upward mobility, again through a correlational lens.

More mechanistically, Moss et al. (2023) employed the MacArthur Scale of Subjective Social Status to analyze how individuals' perceived position in the social hierarchy affects their mental well-being. Drawing on data from the Born in Bradford study, the authors demonstrate that subjective social status mediates the impact of material deprivation on psychological well-being. This approach aligns with our treatment variable—relative financial status—and supports the notion that subjective comparisons may have independent effects beyond objective income.

Together, these works inform our causal model by illustrating how relative economic position, perception of social mobility, and psychosocial mechanisms intertwine to influence mental health. However, causal estimation methods, such as those we propose—using average treatment effect (ATE) or average controlled direct effect (ACDE) - remain largely unexplored in this context, which motivates the present study.

3 Our Data

The dataset we use is the EQLS (European Foundation for the Improvement of Living and Working Conditions [European Foundation], 2015) European Quality of Life Time Series, an open and free-access dataset.

The dataset version we worked with had 79,270 respondents answering 199[1] questions. The question can be clustered into various topics, such as education, employment, demographics, and familial statuses, among other categories. We chose 37 covariates (besides our treatment and outcome variables) and clustered them into these categories-

1. **Demographics**: Core, unchangeable background traits like age, gender, family structure, and country. These lie at the start of the causal chain and help explain differences across individuals without being influenced by other factors.

2. **Health**: Health and physical limitations due to chronic illness. These reflect the individual's functional status and overall well-being.

3. **Living Environment**: Housing conditions, neighbourhood safety, and access to services. These shape everyday life and may influence or moderate how other factors affect outcomes.

4. **Employment**: Current job status, job security, and work-life pressures. This cluster reflects both objective and perceived aspects of labour market participation.

5. **Education**: Highest level of education attained. It may be a key long-term resource that influences employment, income, and other aspects of life.

6. **Satisfaction**: Self-reported satisfaction across major life areas. These variables often act as outcomes or mediators reflecting the subjective quality of life.

Some columns have an extreme tendency not to have available values (NA values), like "Y11_Q7b", which corresponds to "Make it difficult to use long term care services: Quality of care?", has only 264/79,270 non-NA responders. We hypothesize that this is due to the confusing manner in which these questions are phrased.

Dropping columns with over 50% of missing answers and dropping respondents with missing answers, we are left with 30 covariates (in addition to treatment and outcome) and 15,877 respondents. We hypothesize that the dataset size will be sufficient for robust and precise ATE estimation, ultimately answering our question.

[1] The number of actual questions is lower since some questions can be answered deterministically by others (derived variables), so not all 199 are actual questions.

4 Causal Assumptions Made

To identify and estimate the causal effects, we need to make assumptions about the data-generating process. In our case of human sociology, the abstractness of our covariates.

Since we had a large number of covariates, we used the existing covariate groupings to cluster variables that share similar causal connections and belong to the same conceptual category. This allowed us to present a more structured and interpretable version of Pearl's causal DAG[2] without losing essential information (Figure 1). While we did not consult domain experts, our assumptions are grounded in widely accepted causal reasoning and common-sense knowledge about how the chosen covariates relate causally[3].

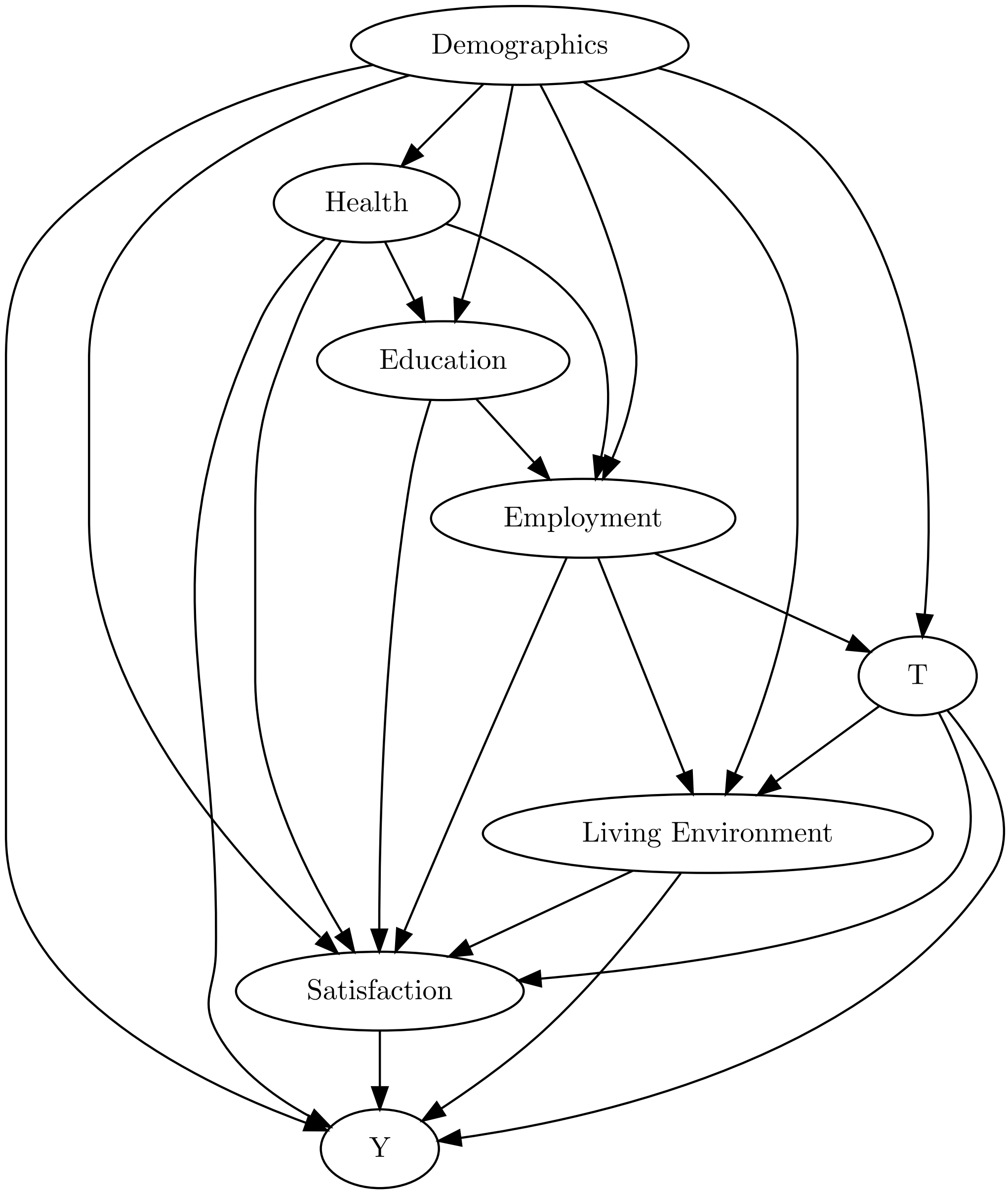

Figure 1: Pearl's causal DAG with covariate clustering.

[2]The original version of the causal DAG without covariate grouping is in here.
[3]These assumptions remain open to interpretation and refinement.

5 Challenges

We believe the main challenge that may affect the analysis is **potential hidden confounding**. For example, personality traits (such as optimism) may influence both financial perceptions and mental well-being, but are not included in the data.

Another possible challenge is the **subjectivity of the treatment**. The treatment is based on the person's response to the question: *"Could you please evaluate your financial situation in comparison to most people in your country?"*. As such, it reflects the person's subjective perception rather than an objective measure of financial status. This introduces potential measurement error, as individuals with similar economic circumstances may rate their relative status differently due to personal bias.

In addition to the subjectivity of the treatment, there is a risk of **reverse causality** — poor mental well-being may lead individuals to perceive themselves as financially worse off, regardless of their actual financial standing. More broadly, since our covariate groups are broad and were defined without input from domain experts, some causal relationships may remain ambiguous. For example, a person's health may be causally influenced by their education level, yet both may fall under different covariate clusters in our model, making it difficult to fully disentangle their roles.

6 Estimation Methods

To estimate the causal effect of perceived relative financial status on mental well-being, we plan to use several established estimation methods, including regression-based approaches (S-learner and T-learner), propensity score-based methods (IPW), and matching.

These methods are appropriate given our identification strategy, which is based on the backdoor criterion. Using our causal DAG, and the backdoor set identification algorithm defined in DoWhy, we identified a minimal set of covariates (1) to adjust for in order to block all backdoor paths from the treatment to the outcome. This allows us to estimate the ATE under the assumption of conditional ignorability.

$$S = \{v \in V \mid V \in \{\text{Employment, Demographics}\} \tag{1}$$

Applying multiple estimation methods—regression-based, propensity score-based, and matching—enables us to evaluate the consistency of results across different frameworks and assess the robustness of our findings. In all approaches, we will adjust for the identified covariates and compare the estimated effects, while also examining overlap, covariate balance, and sensitivity to model specifications.

7 Robustness Checks

To assess the robustness of our causal estimates and validate the credibility and stability of our causal conclusions, we plan to conduct the following analysis:

First, we will evaluate the overlap assumption by inspecting the distribution of propensity scores across treatment groups and applying different levels of trimming to remove samples with extreme or non-overlapping propensity scores.

For matching, we will experiment with alternative distance metrics (e.g., Euclidean, Minkowski, and Manhattan) to evaluate the stability of the estimated treatment effect under different matching schemes.

Additionally, we will conduct subset analyses, such as estimating effects separately for participants from different countries, to assess the consistency of findings across subpopulations.

Finally, we will use the DoWhy package to implement refutation tests, including simulation-based checks where we add random variables (as fake treatments, outcomes, confounders, or hidden confounders) to assess the sensitivity of our pipeline. We will also apply data subsampling to examine how estimates vary across different random subsets of the data.

References

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