Measuring Intergenerational Transmission of Poverty

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The intergenerational transmission of poverty is a complex process, outcomes and family income may both be partly determined by other unobserved individual or household characteristics, such as both parents and child ability or any “neighbourhood’’ effect. Therefore, estimating causal effects in this context is a notoriously difficult task. Because of the complexity of the process, different statistical techniques have been used, each of which relies on a different set of assumptions. The framework of Potential Outcomes approach for causal inference (Neyman, 1923; Rubin, 1974, 1978), considers a randomized experiment where (a) subjects are randomly selected from the target population; (b) a binary treatment is randomly allocated to the subjects; (c) there are no hidden versions of the treatment and there is no interference between units (Stable Unit Treatment Value Assumption - SUTVA) as the ideal setting for estimating causal effects. Following the Rubin Causal Model (RCM), we can consider growing up in a poor household as a “treatment' variable and we can thus study the “treatment effect' of being a poor child on being poor as an adult, estimating the differences between the probability of being poor if the individual grew up in poverty and the probability that the same individual would be poor if he did not grow up in a poor household under the Conditional Independence Assumption (CIA). This is the fundamental problem in causal inference, as we do not have data on what the counterfactual outcome is. Therefore, on one hand, I apply a propensity score matching method to select a control group of non-treated individuals (in this case non poor as a child) who are very similar to treated individuals conditional on a set of observable characteristics (parental characteristics, family composition, and other features fixed in childhood, such as the number of siblings or birth order). The matched samples of poor and non-poor children will then be used to assess impacts on adulthood outcomes, primarily income and poverty.

Moreover, because we are interested on inequality, poverty and inequality of opportunity, we will focus not only in mean impacts estimation, but also in the distributional effects of growing up poor. A natural and relatively simple way to explore differences across the distribution of son's outcomes is through the use of quantile regressions. This flexibility to look across the distribution allows an examination of differences between sons at the top of the outcomes distribution versus sons at the bottom of the outcomes distribution. I will thus also apply to this research question Quantile Treatment Effects (QTE), identified through semi-parametric and non-parametric estimators (Frolich M. and Melly B., 2008, 2010). QTE are a suitable instrument to identify the potentially heterogeneous impacts of variables on different points of an outcome distribution. It seems possible that the linkage across generations differs across the son\'s conditional outcomes distribution.

In this paper I am also examining the causal channels through which being born poor affects the individual's economic and social status as an adult. I aim at analyzing the interplay between growing up in poverty on the children's outcomes later in life, introducing individual human capital as intermediate variable. Accordingly I plan to use a model based on the general framework of principal stratification (Frangakis and Rubin, 2002; Rubin, 2004) to assess if there is any impact of growing up in poverty on children's outcomes later in life after controlling for individual human capital, among the respondents of the PSELL-3/EU-SILC. In a nutshell, if Z_i is the treatment variable, with value equal to 1 in case of growing up in poverty and 0 otherwise, for each individual i, a comparison of causal effects of Z (growing up in poverty) on Y (children's outcomes later in life) for different principal strata defined, by S(0) (individual human capital = 0 if no tertiary education) and S(1) (individual human capital = 1 otherwise), provides information on the extent to which a causal effect of growing up in poverty on children\'s outcomes later in life occurs together with a causal effect of growing up poor on the intermediate outcome human capital status, S.