Occupational choice: The roles of cognitive and non-cognitive skills

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1 Introduction

Occupation decisions are multidimensional and follow a complex mechanism. A huge literature show that, in choosing among many occupations, a worker will choose occupations to maximize the discounted present value of potential lifetime work time and education enables one to move up the job scale (Schmidt and Strauss 1975, Boskin 1974). However, other notable aspect of education choice is the role of self-selection, the uncertainty of education outcomes and labor market, significant heterogeneity among individuals in cognitive and non-cognitive skills. In view of the general interest in skill formation policies, it is important to obtain a measure of the true causal effect of schooling on wages. This. The next section will present background material and review the most important literature on how skills formation affect the career decision of individual

2 Literature Review

A growing literature studies occupational decisions under insights of skill formation and and the potential cross-productivity between cognitive and socio-emotional skills.

Schmidt and Strauss (1975): The Prediction of Occupation Using Multiple Logit Models.

In this paper the author apply the multiple logit model to the prediction of occupation (or type of job) of individuals, based on certain personal characteristics. We begin by examining the effects of four essentially exogenous variables on occupation: race, sex, educational attainment, and labor market experience. Race and sex are zero-one dummies taking on the value one for the more numerous (whites and males) categories. Education is measured in school years, and labor market experience is calculated as age minus years of schooling minus five. Using these explanatory variables, we predict individuals to be in one of five occupational groups: "professional," "white collar," "craft," "blue collar," and "menial. education enables one to move "up" the job scale. evidence of race and sex discrimination, since it argues that existing patterns of employment cannot be explained merely by black-white or male-female differences in education and experience

Cunha and Heckman(2006b):Formulating, Identifying and Estimating the Technology of Cognitive and Noncognitive Skill

In this paper, the authors estimate a linear dynamic factor model that exploits cross equation restrictions (covariance restrictions) to secure identification of a multistage technology for child investment. The authors raise a central problem with the production function approach that is accounting for the endogeneity of inputs. So it is common that in studies of cognitive production, researchers would places great demands on standard instrumental variable (IV) and fixed effect procedures, such as those used by Todd and Wolpin. However, reliance on IV is problematic because of the ever-present controversy about the validity of exclusion restrictions. The CNLSY data used by Todd and Wolpin (2005) and in this paper have a multiplicity of investment measures subsumed in a home score measure which combines many diverse parental input measures into a score that weights all components equally. In term of using test score as output, Todd and Wolpin (2005) and the large literature they cite use a cognitive test score as a measure of output. This imparts a certain arbitrariness to their analysis. Test scores are arbitrarily normed. Any monotonic function of a test score is a perfectly good alternative test score. A test score is only a relative rank. none of these measures is intrinsically satisfactory because there is no meaningful cardinal scale for test scores. Cunha and Heckman(2006b) recommend other anchors a well-defined cardinal scale such as high school graduation, college enrollment, and the like. The finding in this paper: high levels of self productivity in the production of cognitive and non-cognitive skills, evidence of sensitive periods for parental investments in both types of skills with the sensitive period for cognitive skill investments occurring earlier in the life cycle than the sensitive period for investments in non-cognitive skills.

Cunha and Heckman(2007): The Technology of Skill Formation

The paper present a simple model of skill formation and summarize findings of the recent literature on child development and explains them. This paper using nonlinear setting of skill production function (Cunha and Heckman, 2006b) show six stylized facts on human capital development.In contrast with other previous literature, the authors emphasize on the distinguish between early and later investment on cognitive and non-cognitive skills and the obsolete of nature vs nurture theory. In this paper, the authors build a general background on investment profile and focus on estimating self-productivity and complementarity and their implication on policies using empirical results. There are three different policies that has been tested:

- The first policy is a Perry Preschool-like policy. It provides investment at early ages that moves children from the first decile of child cognitive skills at entry age to the fourth decile of child skills at the age of exit from the program. In this policy, there is no follow-up investment

- The second policy is conducted on same target population but it postpones remediation until adolescence (by using college tuition programs, adolescent literacy programs and mentoring programs) that produce approximately the same high school graduation rates but induces higher cost (35% larger than in the Perry Preschool program).

- The final one contrast early-only and late-only investment policies with a third policy that optimally distributes the resources spent in the second policy over the full life cycle of the child. A balanced investment strategy is the most efficient

Christian Belzil (2006): The Return to Schooling in Structural Dynamic Models: A Survey

This paper contains a survey of the recent literature devoted to the returns to schooling within a dynamic structural framework. The authors present a historical perspective on the evolution of the literature, from early static models set in a selectivity framework (Willis and Rosen, 1979) to the recent literature, stimulated by Keane and Wolpin (1997), and which uses stochastic dynamic programming techniques. After reviewing the literature thoroughly, the paper compare the structural approach with the IV (experimental) approach. In details, most structural estimates reported for the US range between 4% and 7% per year. On the other hand, IV estimates between 10% and 15% per year are often reported. The discrepancy prevails even when comparable (if not identical) data sets are used. The discussion is focused on understanding this divergence. The distinction between static and dynamic model specifications is a recurrent theme in the analysis.