

**Skills over the Life Cycle: Evidence from the United States
and the Philippines**

A DISSERTATION
SUBMITTED TO THE FACULTY OF THE
UNIVERSITY OF MINNESOTA
BY

JUAN CAMILO CHAPARRO

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

JOSEPH RITTER

AUGUST 2016

© Juan Camilo Chaparro 2016
ALL RIGHTS RESERVED

Acknowledgements

I am deeply grateful to my adviser, Joseph Ritter. Joe provided constant advice and thoughtful conversations. He was strict and kind. He guided me in the long process of creating my own research agenda. I have learned from him, through his example in academic and everyday situations, the attributes of the professional academic that I would like to become.

Aaron Sojourner also played a fundamental role. Aaron helped me in many ways as a student, for which I am filled with gratitude. We worked together in the research paper included as the fourth chapter in this dissertation. I am also grateful to Marc Bellemare and Paul Glewwe, members of my dissertation committee. Their feedback and suggestions were fundamental throughout the entire process. The Center for International Food and Agriculture Policy (CIFAP) provided the necessary economic support to collect data used in the third chapter.

Johanna Fajardo-Gonzalez has been my beloved partner for all these years. This dissertation was possible thanks to her extraordinary support. I also thank my parents, Luis Alfonso and Rosita, for their sacrifice, love and faith. Santiago Suarez rescued me during my darkest hour. Finally, I would like to thank my friends and colleagues who made my life as a graduate student a remarkable experience.

Dedication

To my parents, Rosita Cardona and Luis Alfonso Chaparro. Muchas gracias por la constante ayuda y por creer en mí.

Contents

Acknowledgements	i
Dedication	ii
List of Tables	vi
List of Figures	ix
1 Introduction	1
2 Occupational Choice and Returns to Skills: Evidence from the NLSY79 and O*Net	3
2.1 Introduction	3
2.2 Theoretical Framework	6
2.2.1 The environment	6
2.2.2 The Worker Selection Problem	8
2.2.3 The Occupational Choice Problem	10
2.3 Data	13
2.3.1 The Occupational Information Network (O*Net)	13
2.3.2 National Longitudinal Study of Youth (NLSY79)	17
2.3.3 Relative Math and Language Skills	21

2.4	Econometric Model	22
2.5	Results	25
2.5.1	First stage regressions	25
2.5.2	OLS and IV models	27
2.6	Concluding Remarks	29
3	Gender differences in occupational aspirations, occupational choices and returns to skills: evidence from the Philippines (CLHNS)	47
3.1	Introduction	47
3.2	Literature Review	49
3.3	Cebu Longitudinal Health and Nutrition Survey (CLHNS)	53
3.4	Survey of Filipino psychologists	59
3.5	Econometric Framework	65
3.6	Results	66
3.7	Conclusions and Discussion	69
4	Same Program, Different Outcomes: Understanding Differential Effects from Access to Free, High-Quality Early Care	79
4.1	Introduction	79
4.2	Conceptual Framework	86
4.2.1	An Economic Model of Post-natal Investment	87
4.2.2	Optimal Post-natal Investment and Economic Interpretation	92
4.3	Data and Variables	95
4.3.1	Factors Examined for Heterogeneity in Effects: Potential Wage (\hat{w}), pre-natal investment level (\mathbf{I}_0^*), and child's endowment (ϕ)	95
4.3.2	Measures of Postnatal Choices	101
4.4	Results	103

4.5	Limitations	112
4.6	Conclusion	113
4.7	Figures	116
4.8	Tables	122
Bibliography		133
Appendices		141
A1	Job market equilibrium	141
A2	Crosswalks and merged O*NET / NLSY79 data	143
A3	First stage regressions - Relative Skills	146
A4	Regression tables from 1992 to 2012	148
A5	Other longitudinal studies	155
A6	Instructions given to Filipino respondents	158
A7	Kuhn-Tucker conditions for the post-natal parental problem	160
A8	Measurement of quality of non-maternal care (q^n)	161
A9	Supplementary Tables and Figures - Chapter 4	163

List of Tables

2.1	An example: skill content and average skills for two occupations	30
2.2	Summary Statistics, 1992	31
2.3	Summary Statistics, 2000	33
2.4	Summary Statistics, 2010	35
2.5	First Stage - Current Occupation O*Net Score: Math (r_k^M)	37
2.6	First Stage - Current Occupation O*Net Score: Language (r_k^L)	39
2.7	OLS and IV models - Ln of Hourly Rate of Pay ($\epsilon = 0.25$)	41
2.8	OLS and IV models - Ln of Hourly Rate of Pay ($\epsilon = 0.50$)	43
2.9	OLS and IV models - Ln of Hourly Rate of Pay ($\epsilon = 0.15$)	45
3.1	Summary of the CLHNS (Philippines)	55
3.2	Intraclass correlation coefficients	63
3.3	Summary Statistics, Women Subsample	71
3.4	Summary Statistics, Men Subsample	71
3.5	Differences between women and men	72
3.6	First Stage Results: ONet Ratings, Women subsample	73
3.7	First Stage Results: ONet Ratings, Men subsample	74
3.8	First Stage Results: Filipino Ratings, Women subsample	75
3.9	First Stage Results: Filipino Ratings, Men subsample	76

3.10	OLS and IV Wage Equation Results: Filipino Ratings, Women subsample . . .	77
3.11	OLS and IV Wage Equation Results: Filipino Ratings, Men subsample . . .	78
4.1	Possible caretakers and effective units of care provided	123
4.2	Summary statistics for variables in the potential wage model (\hat{w})	124
4.3	Estimates from Heckman selection model in CPS sample	125
4.3	Estimates from Heckman selection model in CPS sample (continued...) . . .	126
4.4	Estimates from Heckman selection model in CPS sample	127
4.5	Estimates from SUR model for pre-natal investment using the ECLS-B sample	128
4.6	Summary statistics	129
4.7	Learning an Literacy components (IT-Home score) available in the IHDP sample	130
4.8	Treatment effect of the IHDP intervention on cognitive development	131
4.9	Treatment effect of the IHDP intervention on inputs in the production of cognitive skills	132
A1	From 6-digit SOC 2000 to 4-digit Census 2000: the case of Electrical and Electronic Engineers.	144
A2	First Stage - Relative Math Skills ($p_i^M - \bar{p}_{k,\epsilon}^M$)	146
A3	First Stage - Relative Language Skills ($p_i^L - \bar{p}_{k,\epsilon}^L$)	147
A4	OLS models - Ln of Hourly Rate of Pay	149
A5	IV models - Ln of Hourly Rate of Pay	150
A6	First Stage - Current Occupation O*Net Score: Math (r_k^M)	151
A7	First Stage - Current Occupation O*Net Score: Language (r_k^L)	152
A8	First Stage - Relative Math Skills ($p_i^M - \bar{p}_{k,\epsilon}^M$)	153
A9	First Stage - Relative Language Skills ($p_i^L - \bar{p}_{k,\epsilon}^L$)	154
A10	Summary of the IFLS (Indonesia)	156

A11	Summary of the MxFLS (Mexico)	157
A12	Descriptive statistics from the NICHD – SECCYD data	166
A13	Model estimates for the quality of non-maternal care in the SECCYD – NICHD data	167
A13	Model estimates for the quality of non-maternal care in the SECCYD – NICHD data (continued...)	168
A14	Treatment effect at 12 months on HOME score and Bayley test	169

List of Figures

2.1	Standardized Math Knowledge, Importance Scores, 418 4-digit Census 2000 Occupations	16
2.2	Standardized English Language Knowledge, Importance Scores, 418 4-digit Census 2000 Occupations	17
2.3	Math and Language Knowledge, Importance Scores, 418 4-digit Census 2000 Occupations	18
3.1	Top ten categories in occupational aspirations (1998)	57
3.2	Top ten categories in occupational choices (2005)	58
3.3	Standard error of the mean: math and reading skills	62
3.4	Average rating by Filipino psychologists, math and reading skills (292 occupations)	64
4.1	Distribution of pre-natal investment and endowment indexes, ECLS-B and IHDP samples	117
4.2	Predicted IQ at 36 months for IHDP treatment and control groups	117
4.3	IHDP treatment effects on IQ at 36 months	118
4.4	IHDP treatment effects on hours per week of CDC use (t)	118
4.5	IHDP treatment effects on hours per week of non-maternal care (n)	119
4.6	IHDP treatment effects on hours per week of -maternal care (r)	119
4.7	IHDP treatment effects on work hours (L)	120
4.8	IHDP treatment effects on leisure time (l)	120

4.9	IHDP treatment effects on quality of maternal care (q^r)	121
4.10	IHDP treatment effects on quality of non-maternal care (q^n)	121
A1	Heterogeneity in treatment effects on Age 8 IQ	164
A2	Heterogeneity in treatment effects on Age 8 IQ	164
A3	Heterogeneity in treatment effects on Age 18 IQ	165

Chapter 1

Introduction

The development of human skills is a life-long process. The dynamic of skill formation is critical to understand fundamental labor market outcomes, such as employment histories and wage profiles. Skills and occupational choices are profoundly related. A fundamental idea throughout this dissertation is that it possible to infer information about skill acquisition from occupational choices. Furthermore, such inferred information can be used to study the socio-economic causes and consequences of skill formation.

Chapter 2 explores the skill content of occupational choices in the United States. The goal of the chapter is to measure the wage return to math and language skills, taking into account the self-selection process of occupational choice. Occupations must be treated as endogenous variables in any wage equation. To deal with the endogeneity of occupations, I instrument the importance of math for a worker's occupation in her thirties and forties (occupational choices) with the importance of math for the worker's preferred occupation back in her early twenties (occupational aspirations). A similar instrumental variable is proposed for language skills. This empirical strategy is possible after the combination of data from the National Longitudinal Study of Youth, 1979 Cohort (NLSY79) and the Occupational Information Network (O*Net).

The Occupational Information Network reports key characteristics for more than 800 occupational categories, relevant for the United States, using more than 400 variables. In addition, O*Net data are publicly available and well documented, but there is no equivalent data source for developing countries. Chapter 3 proposes a cost-effective methodology to collect information on a limited subset of O*Net variables. I implemented the methodology in the Philippines by hiring the professional services of ten industrial psychologists. I combine these novel data with information from the Cebu Longitudinal Health and Nutrition Survey (CLHNS) to study gender differences in occupational aspirations, occupational choices and returns to skills.

The last chapter in this dissertation explores the early stages of skills formation. It proposes an economic model to understand the effects of the Infant Health and Development Program (IHDP), an intervention done in the United States during the mid 80s which had the purpose of promoting the physical, social and mental development of premature infants. The chapter analyses the consequences of access to free and high-quality childcare services on time allocation and other inputs of the technology of early skill formation. In conclusion, this dissertation uses data from two different countries and studies three different stages of human skill development along the life cycle. It demonstrates the research value of occupational choices as a powerful source of information about human capital accumulation. My future research agenda will focus on expanding the ideas and methodologies discussed in this document.

Chapter 2

Occupational Choice and Returns to Skills: Evidence from the NLSY79 and O*Net

2.1 Introduction

The U.S. economy had around 137 million jobs in May 2015, which the Bureau of Labor Statistics classified into hundreds of occupational categories. There were approximately 610,000 lawyers, 178,000 electrical engineers, 129,000 head chefs and 1.1 million restaurant cooks. In total, 840 detailed occupational categories were used in the most recent issue of the Occupational Employment Statistics ([BLS, 2015](#)). The United States has rich data on the past and present occupational choices of its workforce.

Various sociological and psychological theories argue that work life, and occupations in particular, can be an important part of a person's identity ([Budd, 2011](#), Chapter 9). In addition, occupations implicitly carry substantial information about a worker's human

capital. For example, all practicing lawyers and physicians finished professional school, electrical engineers have at least a college degree, and head chefs have more work experience than regular cooks. There is valuable information embedded in occupational choices.

The goal of this paper is to use occupational choices in the process of measuring the wage return to a set of human skills. There are two possible channels through which skills might affect productivity and wages: first, the set of occupations available to an individual is influenced by her skill portfolio (*occupational sorting*). Second, the value of a worker's set of skills could depend on her relative position when compared to her peers and competitors in the labor market (*relative proficiency*). This paper attempts to measure the contribution of both channels to the total wage return. To do so, I combine data from the National Longitudinal Study of Youth, 1979 cohort (NLSY79), with information from the Occupational Information Network (O*Net).

The main challenge that has to be addressed is the self-selection of workers into their occupation (Roy, 1951; Heckman and Honore, 1990). For this reason, occupations have to be treated as endogenous regressors in wage equations. The NLSY79 has followed a cohort of respondents since 1979, when they were on average 18 years old. Respondents were asked in 1979 and 1982 about their occupational aspirations for age 35.¹ This paper explores the validity of using characteristics of the occupation to which someone aspired to in her early twenties (occupational aspirations) as instruments of the characteristics of the occupations performed by the same individual during her thirties and forties (occupational choices).

What are the main characteristics of any occupation? Can occupations be measured and compared to one another? The research by industrial and organizational psychologists who have explored these questions is the foundation of the Occupational Information Network, known as O*Net (Peterson et al., 2001). O*Net describes in detail the skills, abilities, tasks

¹Respondents were asked the following question: "What kind of work would you like to be doing when you are 35 years old?". Aspirations and Expectations Questionnaire, Question 1 (Section 22 in 1979 and Section 17 in 1982). The most common answers were manager, secretary, registered nurse, accountant, and computer programmer. All answers were classified into approximately 300 occupational codes.

and educational requirements of all the occupations in the U.S. economy.

I processed the O*Net data to create a standardized measure of the importance of math and language skills for each occupation, following the methodology proposed by [Acemoglu and Autor \(2011\)](#). Both standardized measures were used to score workers' occupational choices and their occupational aspirations in the NLSY79 data. The richness of the data allows me to instrument the importance of math for a worker's occupation in 2012, for example, with the importance of math for the occupation she aspired to back in 1982. A similar instrument is proposed for language skills. The empirical strategy followed in this paper addresses the following questions: How large is the wage return to math and language skills due to occupational sorting? Has the return changed as the cohort aged? How does it compare to the wage return due to relative proficiency in math and language skills?

Since its origins, Human Capital Theory has conceptualized human capital as a unidimensional stock built through investment in time-consuming activities ([Ben-Porath, 1967](#); [Becker, 1993](#)). Since human capital was regarded as unidimensional, it was appropriate to consider years of education as the best indicator of human capital accumulation. In consequence, applied research focused for many years on the economic returns to schooling ([Mincer, 1974](#); [Griliches, 1977](#); [Card, 2001](#)). More recently, human capital has been redefined as multidimensional; a collection of different human skills ([Cawley, Heckman, and Vytlačil, 2001](#); [Bowles, Gintis, and Osborne, 2001](#)).

There is evidence that both cognitive and socio-emotional skills determine multiple labor market outcomes, including occupational choice ([Heckman, Stixrud, and Urzua, 2006](#); [Cobb-Clark and Tan, 2011](#); [Almlund et al., 2011](#)), but most of the literature is based on broad occupational categories: [Heckman, Stixrud, and Urzua \(2006\)](#) used only two groups (blue-collar and white-collar jobs), whereas [Cobb-Clark and Tan \(2011\)](#) created 18 groups. This paper uses 420 occupational categories available in the combined NLSY79 - O*Net data, based on three different Census classification systems (1970, 1980 and 2000). It is appropriate to use narrow occupational categories, in which lawyers, nurses and electrical

engineers are distinguished from one another, in order to extract the valuable information about human skills carried by occupational choices.

This chapter has the following structure: Section 2.2.1 presents a definition of occupations in terms of the skills involved as the starting point of the theoretical framework. The theoretical framework also defines the economic problems faced by firms (Section 2.2.2) and workers (Section 2.2.3). The O*Net data is explained in Section 2.3.1 and the key traits in the NLSY79 data are discussed in Section 2.3.2. The econometric framework is explained in Section 2.4. After combining both datasets, each occupation becomes a two-dimensional vector of math and language skills. Estimation results and the decomposition of total wage returns are discussed in Section 2.5. Section 2.6 concludes.

2.2 Theoretical Framework

Workers self-select into their occupations. Each worker decides which occupation she would like to perform, given her skills and the options available to her. Any attempt to use occupational choices for inference must take into account that occupations are endogenous in a wage equation. The main goals of the following model are to emphasize the endogeneity of occupational choice, to motivate a possible solution based on instrumental variables, and to define the notation used in the rest of the paper. The model is based on Roy (1951), Rosen (1986), Kremer (1993) and Lazear (2009).

2.2.1 The environment

Individuals are characterized by a set of social and demographic traits such as age, gender and race. Denote these variables for individual i as vector X_i . Each individual also has a set of skills that she could offer in the labor market. Individual i has a **proficiency level** of p_i^s in skill s and there are S skills in total. Therefore, vector $(X_i, p_i^1, \dots, p_i^S)$ fully describes

each individual before facing any decision-making process.

Denote by r_k^s the importance of skill s for performing occupation k . I will refer to vector (r_k^1, \dots, r_k^S) as the **skill profile vector** for occupation k . Assume there is a one-to-one correspondence between occupations and skill profiles. When a worker chooses an occupation, she is choosing a specific skill profile vector and vice versa. Let Λ be a compact subset of \mathbb{R}_+^S , representing the set of available occupations. The set of available occupations depends on the level of development and economic structure of the economy. Therefore, individuals take the set of available occupations as given and their chosen occupation must be an element of Λ .

As in [Rosen \(1986\)](#), labor market transactions have a double purpose, because skills and occupations are traded simultaneously. There is a market for skills, where firms look for the appropriate worker for each occupation; at the same time, individuals look for their preferred occupation in a market for occupations. Workers and firms play opposite roles in each one of these markets. I model the economic behavior of firms through a worker selection problem (Section 2.2.2). The economic behavior of individuals is explained using an occupational choice problem (Section 2.2.3).

Let w_i^k be equal to the wage that worker i would obtain if she was employed in occupation k . As in [Roy \(1951\)](#), we cannot observe counterfactual wages, although they are well defined and play a fundamental role in labor market equilibrium. The wage should depend on the skills of the worker, as well as the characteristics of the occupation. Let $W(p_i^1, \dots, p_i^S, r_k^1, \dots, r_k^S)$ be the wage function that has such property. It is the outcome of equilibrium conditions for skills and occupations. Both equilibrium conditions are defined in [Appendix A1](#) (job market equilibrium).

2.2.2 The Worker Selection Problem

Consider the economic problem faced by firms. A firm has a job opening in a particular occupation and it will look for the most appropriate candidate to fill the position. The output generated by the worker will depend on the interaction between her individual skills and the characteristics of the occupation. I will follow [Kremer \(1993\)](#) and use a modified O-Ring production function to model such interaction.

Let $q_{i,k}^s$ be the probability that worker i performs correctly the tasks associated with skill s , if she is hired to work in occupation k . More able workers should be less prone to making mistakes, but worker's ability is relative to the occupation. A measure of this idea is the ratio between the worker's proficiency in skill s and the importance of the same skill for the occupation, p_i^s/r_k^s . Therefore, $q_{i,k}^s = h(p_i^s/r_k^s)$, where $h : (0, \infty) \rightarrow (0, 1)$ and $h'(\cdot) > 0$.²

The quality of the job match is defined as $\prod_{s=1}^S q_{i,k}^s$.³ The quality of a match depends not only on how proficient the worker is on different labor skills, but also on how relevant these skills are for the occupation. This is the main reason why I differentiate between the vector of individual proficiency (p_i^1, \dots, p_i^S) and the skill profile vector (r_k^1, \dots, r_k^S) . [Lazear \(2009\)](#) postulated a similar idea, but in his model skill requirements are specific to firms rather than occupations.

Finally, let $B(r_k^1, \dots, r_k^S) > 0$ be the maximum value of output produced by a worker in occupation k who makes no mistakes. I assume the maximum output is non-decreasing in each one of the elements of the skill profile vector ($\partial B / \partial r_k^s \geq 0, \forall s$). We can now formulate the worker selection problem:

²I rule out $p_i^s = 0$ and $r_k^s = 0$ as possible cases, but it is important to define the behavior of function h under both limiting cases. In the first case, if a worker has very poor skills of type s , then the probability of performing correctly the related tasks should tend towards 0. Therefore, $\lim_{p \rightarrow 0} h(p/r) = 0$. In the second case, if skill s is not important for performing a given occupation, then the quality of the job match should not be affected by the skill proficiency of the worker. Thus, $\lim_{r \rightarrow 0} h(p/r) = 1$.

³The quality of the job match ranges between 0 and 1. It is similar to the probability of successful production in [Kremer \(1993, p. 553\)](#).

$$\begin{aligned} & \text{Max}_{p_i^1, \dots, p_i^S} \left(\prod_{s=1}^S q_{i,k}^s \right) B(r_k^1, \dots, r_k^S) - W(p_i^1, \dots, p_i^S, r_k^1, \dots, r_k^S) \\ & \text{s.t.} \quad q_{i,k}^s = h(p_i^s / r_k^s) \quad \forall s \in \{1, \dots, S\} \end{aligned}$$

The wage function W is a component in this choice problem as well as in the occupational choice problem and is the result of the job market equilibrium explained in Appendix A1. The solution to the worker selection problem is characterized by the following set of S first order conditions:

$$\underbrace{h'(p_i^s / r_k^s)}_{(a)} \frac{1}{r_k^s} \overbrace{\left(\prod_{s' \neq s} q_{i,k}^{s'} \right) B(r_k^1, \dots, r_k^S)}^{(b)} = \frac{\partial W}{\partial p_i^s}, \quad \forall s \in \{1, \dots, S\} \quad (2.1)$$

Hiring a worker who is more able on skill s has two consequences on production. First, it increases the probability that the worker does a better job on the tasks associated with the skill. The change in probability is equal to segment (a) in the first order condition for p_i^s . Second, the expected value of the output associated with the other $S - 1$ skills also increases, due to the complementarity nature of the O-Ring production function, as explained by [Kremer \(1993\)](#). This second change occurs in segment (b) of the remaining $S - 1$ first order conditions. The marginal cost of hiring a more able worker in skill s is given by $\partial W / \partial p_i^s$.

The solution to the worker selection problem is given by S functions that pin down the skill proficiency vector of the hired worker,

$$p_i^{*s} = P^s \left(r_k^1, \dots, r_k^S; B, h, W \right), \quad \forall s \in \{1, \dots, S\} \quad (2.2)$$

Therefore, the characteristics of the hired worker $(p_i^{*1}, \dots, p_i^{*S})$ will depend on the skill profile of the occupation she is hired to perform (r_k^1, \dots, r_k^S) , the maximum value of the output generated by the occupation (B) and function h . The wage function W and its properties also determine the characteristics of the hired worker.⁴

2.2.3 The Occupational Choice Problem

Individual preferences are represented by the following utility function:

$$U(c_i, r_k^1, \dots, r_k^S; p_i^1, \dots, p_i^S, X_i) = u(c_i) - C(r_k^1, \dots, r_k^S; p_i^1, \dots, p_i^S, X_i)$$

Utility can be broken down in two parts. The first one is an increasing and concave function of consumption (c_i). The second part is the effort cost derived from choosing and working in a particular occupation, called function C . Note that the effort cost function depends on the proficiency of the worker in every skill and the skill profile vector of the desired occupation. It also depends on the set of social and demographic characteristics of the individual (X_i).

Function C is analogous to the effort cost function used in signaling models of education (Spence, 1973). In a classical Roy model, workers choose their occupation using an income-maximizing rule. Following a suggestion by Heckman and Honore (1990), I allow workers to take into account non-wage dimensions of work through function C . Some further assumptions of the effort cost function are the following:

- $\frac{\partial C}{\partial p_i^s} < 0, \forall s$: the effort cost of performing any given occupation is decreasing in the skill level of the worker.

⁴Appendix A1 defines the supply of skills available in the market. I assume that the market is thick enough for firms to find a worker with the desired combination of skills, $(p_i^{*1}, \dots, p_i^{*S})$, as long as firms are willing to pay the equilibrium wage rate given by function W .

- $\frac{\partial C}{\partial r_k^s} > 0, \forall s$: performing occupations which are more demanding require higher effort.

Finally, note that the environment has no time or explicit effort dimension. These are simplifying assumptions, but some components in the model could be interpreted as time or effort choices. In particular, the time and effort required to perform each occupation could be embedded in cost function C . If that is the case, then occupations that require more hours of work or additional effort will generate an additional utility cost. This assumption implies that the model allows for heterogeneity in work time or exerted effort across occupations and not within occupations.

We now have all the elements to define and solve the occupational choice problem faced by workers:

$$\text{Max}_{c_i, r_k^1, \dots, r_k^S} u(c_i) - C(r_k^1, \dots, r_k^S; p_i^1, \dots, p_i^S, X_i)$$

$$\text{s.t.} \quad c_i \leq W(p_i^1, \dots, p_i^S, r_k^1, \dots, r_k^S)$$

$$(r_k^1, \dots, r_k^S) \in \Lambda \subset \mathbb{R}_+^S \quad c_i > 0$$

The worker decides the best possible occupation by choosing an optimal skill profile vector $(r_k^{*1}, \dots, r_k^{*S} \in \Lambda)$. Assuming an interior solution, this vector should comply with the following S first order conditions:

$$\frac{du}{dc_i} \frac{\partial W}{\partial r_k^s} - \frac{\partial C}{\partial r_k^s} = 0, \quad \forall s \in \{1, \dots, S\} \quad (2.3)$$

These equations represent a balance between the benefits and the costs of choosing occupations with different skill profiles. For example, if a worker decides to migrate into an

occupation where skill s is more important, that would imply an additional effort cost of $\partial C/\partial r_k^s$, but the decision would also represent additional labor income of $\partial W/\partial r_k^s$, which would be valued at the marginal utility of consumption, du/dc_i .

The system of first order conditions in (2.3) describes optimal occupational choice, by the implicit determination of the optimal skill profile vector $(r_k^{*1}, \dots, r_k^{*S})$. Therefore, there is a system of S implicit functions which drive the demand in the market for occupations (See Appendix A1):

$$r_k^{*s} = R^s \left(X_i, p_i^1, \dots, p_i^S; u, W, C \right), \forall s \quad (2.4)$$

Occupational choice depends on the individual's social and demographic characteristics (X_i), the proficiency of the individual in all skills (p_i^1, \dots, p_i^S), and the functional forms of the utility function (u), the wage equation (W) and the effort cost function (C).

Let $w_i^{k^*}$ be the actual wage earned by worker i and k^* her chosen occupation. $w_i^{k^*}$ corresponds to wage data that could actually be collected. The observed wage will depend on optimal occupational choices:

$$w_i^{k^*} = W(p_i^1, \dots, p_i^S, r_k^{*1}, \dots, r_k^{*S}) \quad (2.5)$$

As in a classical Roy model, this theoretical framework distinguishes between observed and counterfactual wages. Observed wages ($w_i^{k^*}$) correspond to the wage function (W) evaluated at the optimal occupational choice. Counterfactual wages for any given worker could be calculated in theory using the same wage function.

2.3 Data

2.3.1 The Occupational Information Network (O*Net)

There is a key implicit assumption in the theoretical framework: any occupation can be translated into a skill profile vector (r_k^1, \dots, r_k^S) . I use the Occupational Information Network database to implement this idea (it is publicly available and funded by the U.S. Department of Labor). The O*Net research team collects information about the characteristics of 861 occupations for the U.S. economy. Occupations are classified using the O*NET-SOC taxonomy, which is a refinement of the Standard Occupational Classification system (SOC).

Occupations are analyzed using the O*Net Content Model, which synthesizes decades of research in the field of industrial psychology (Peterson et al., 2001). According to this model, an occupation can be described in full detail by considering its tasks and work activities, previous knowledge and educational requirements, all skills and abilities involved, and some other key characteristics. For a full description of the Content Model, see U.S. Department of Labor (2010). There are in total 239 descriptors per occupation, not including occupation-specific tasks.

The questionnaires on skills and abilities are filled out by job analysts, who are mostly industrial psychologists specialized in human resource management. All the other questionnaires in the O*Net program are answered either by job incumbents or occupational experts, with an average of 30 respondents per occupation. Job incumbents are workers who perform the occupation at the time of survey. Occupational experts are members of professional associations who know specific details for a group of related occupations.

I reviewed all 239 descriptors and selected those included in questionnaires answered only by job incumbents and which were related to math or language skills. Only two descriptors comply with these conditions: 1) Mathematics, from the Knowledge domain and 2) English Language, also from the Knowledge domain.

O*Net data is collected using “behaviorally anchored rating scales” (Peterson et al., 2001, pg. 474). Each job incumbent first answered how important are math skills for their own occupation on a scale from 1 (not important) to 5 (extremely important). The answer is called the **importance score**.

If the respondent considered that math skills have at least some importance (importance score of 2, 3, 4 or 5), then he had to rate the skill level that is required for any worker to have a good performance in the occupation. This score is called the **level rating**, and it ranges from 1 (lowest) to 7 (highest). The question used by the O*Net research team to collect information about knowledge of the English language has the same structure.

O*Net generates publicly-available databases with the average and the standard error of the mean. A new version of the database is released every year and approximately 100 occupations are updated in every release. The database reports **importance scores** and **level ratings** for hundreds of occupations. The publicly-available scores have been rescaled to range between 0 and 100 and correspond to averages across all respondents (National Center for O*Net Development, 2016).⁵

There are two main occupational classification systems in the United States: the Standard Occupational Classification (SOC) and the Census Classification (Census). The SOC is more detailed than the Census system: the 2010 SOC defines 840 detailed occupations, whereas the 2000 Census system encompasses around 400 occupational codes. In general, an occupation in the Census system corresponds to one or more occupational codes under the SOC system.⁶ The O*Net uses a variation of the SOC system and the NLSY has recorded occupational choices following three different versions of the Census system (1970, 1980 and 2000). Therefore, O*Net data have to be aggregated into broader categories and

⁵In 2010, the National Research Council gathered a panel to analyze the research soundness of O*Net. The panel concluded that it is a valuable research tool and the U.S. Department of Labor should continue to finance it. I will follow the advice of Juan Sanchez and David Autor, members of the panel, and use the importance scores for empirical analyses (National Research Council, 2010, pp. 195 - 197).

⁶For example, Electrical Engineers and Electronic Engineers have different occupational codes under the SOC system (17-2071 and 17-2072, respectively). Workers from both occupations are classified under the same code in the Census system (1410).

transformed into the Census classification system.

[Acemoglu and Autor \(2011\)](#) proposed a methodology to aggregate O*Net data and transform it into Census codes. Their key insight was the use of total employment within each SOC occupation as weights. Employment data come from the Occupational Employment Statistics (OES). Thus, the standardized math and language score for each Census occupation is equal to a weighted average of the importance score of those SOC occupations linked to the Census code through an appropriate crosswalk. There are six steps in the process:

- Step 1: transform 8-digit O*NET-SOC 2010 codes into 6-digit SOC 2010 codes.
- Step 2: transform 6-digit SOC 2010 codes into 6-digit SOC 2000 codes.
- Step 3: aggregate 6-digit SOC 2000 O*Net data into 4-digit Census 2000 occupational codes, using the SOC-Census crosswalk created by [Acemoglu and Autor \(2011\)](#).
- Step 4: transform 4-digit Census 2000 codes into 4-digit Census 1990 codes.
- Steps 5 and 6: transform 4-digit Census 1990 codes into 3-digit Census 1980 and 1970 codes.

Appendix [A2](#) explains each step in detail, cites the appropriate crosswalks and provides examples.

The histogram for the standardized math knowledge scores can be found in [Figure 2.1](#). A similar graph for the standardized English language knowledge scores is shown in [Figure 2.2](#). For example, the math knowledge required by electrical engineers is approximately two s.d. above the average for the entire U.S. workforce. As an opposite case, the math knowledge requirement for dishwashers is 1.93 s.d. below the average.

Consider now [Figure 2.2](#). Lawyers perform an occupation with very high language requirements, as the English language score for this occupation is 2.28 s.d. above average.

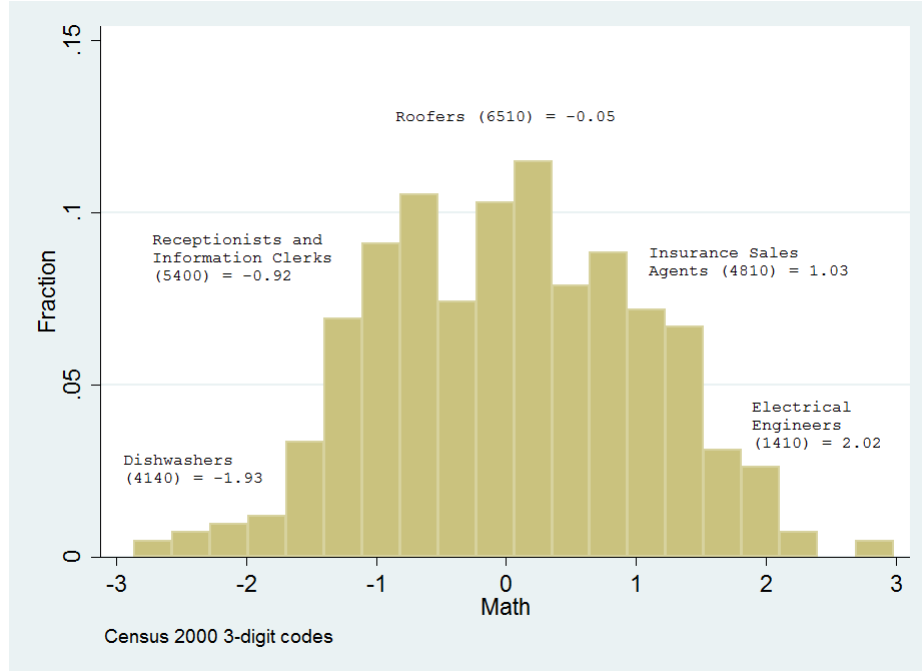


Figure 2.1: Standardized Math Knowledge, Importance Scores, 418 4-digit Census 2000 Occupations

Dishwashers are again on the opposite side of the distribution, with a language score equal to -2.08 s.d.

Using these scores, Figure 2.3 plots occupations in a two-dimensional space of math and language skills. Figure 2.3 can be interpreted using the theoretical framework. Let $S = \{L, M\}$, stand for Language and Math skills. $K = 418$ is the number of occupational codes plotted in the figure. In this case, the set of available occupations is a subset of \mathbb{R}^2 ($\Lambda \subset \mathbb{R}^2$) and each occupation (k) corresponds to a two-dimensional profile vector of language and math skills, which must be an element of the set of available occupations ($(r_k^L, r_k^M) \in \Lambda$). When workers solve the Occupational Choice Problem (Section 2.2.3), they choose a vector (r_k^L, r_k^M) in the space depicted in Figure 2.3.

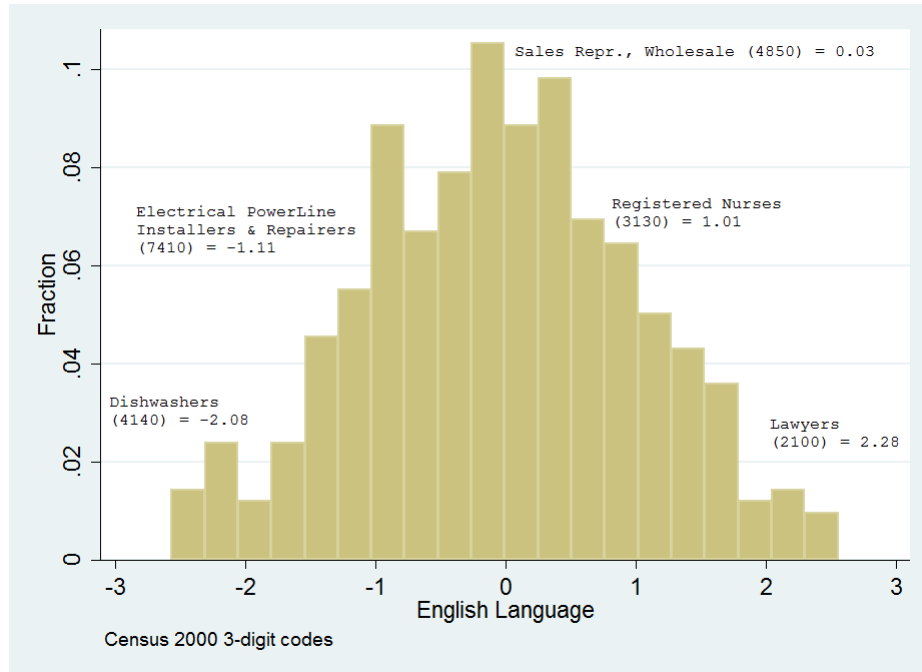


Figure 2.2: Standardized English Language Knowledge, Importance Scores, 418 4-digit Census 2000 Occupations

2.3.2 National Longitudinal Study of Youth (NLSY79)

The NLSY79 has followed individuals born between 1957 and 1964 since the late 1970s. Due to the original sample design and the evolution of the sample, Hispanics and African-Americans who lived in economically disadvantage households in 1979 are over-represented. The original sample size was 12,686 individuals, who were interviewed for the first time in 1979. Annual interviews were conducted until 1994 and data has been collected every two years since 1996.⁷

In 1980, respondents answered the Armed Services Vocational Aptitude Battery tests (ASVAB), which comprised 10 different questionnaires. The Armed Forces Qualification

⁷The NLSY79 had three original subsamples: 1) 6,111 individuals who represented the noninstitutionalized civilian population living in the United States in 1979, born between January 1957 and December 1964; 2) 5,295 respondents with the same age range but living in economically disadvantage households, called the supplemental sample. The supplemental sample included Hispanics, African-Americans and Whites; 3) 1,280 individuals sampled from the US military active members, born between January 1957 and December 1961. For more information, see [Bureau of Labor Statistics \(2012\)](#).

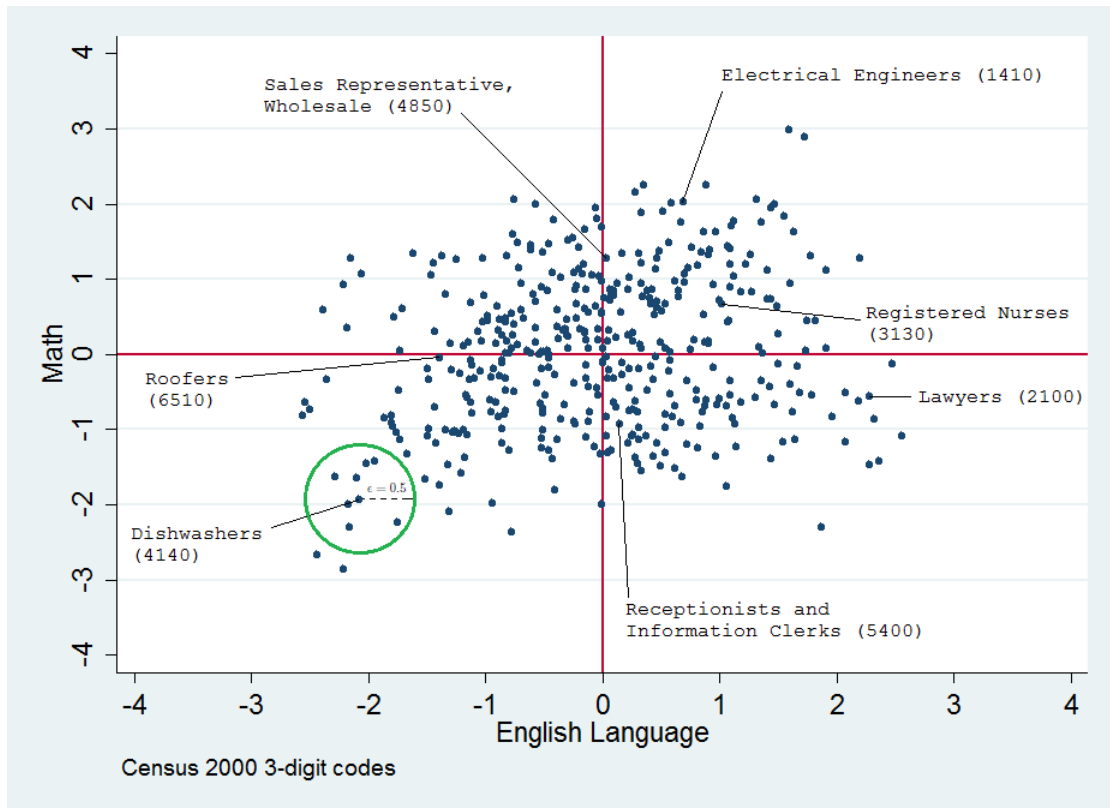


Figure 2.3: Math and Language Knowledge, Importance Scores, 418 4-digit Census 2000 Occupations

Note for Figures 2.1, 2.2 and 2.3: based on O*Net data (Version 16) and SOC-Census crosswalks from [Acemoglu and Autor \(2011\)](#). The units are standard deviations among the U.S. employed population of the importance score.

Test (AFQT) is based on four of them: Word Knowledge, Paragraph Comprehension, Arithmetic Reasoning and Mathematics Knowledge. The AFQT score has been used before as a measure of skills acquired before entering the labor market (Neal and Johnson, 1996). The NLSY79 research team processed the ASVAB data to take into account the age differences of respondents (Bureau of Labor Statistics, 2012). Thus, age-appropriate math (p_i^M) and language (p_i^L) Z-scores are included in the publicly available data.⁸

The NLSY79 cohort answered a short version of Rotter’s locus of control instrument in 1979 (Rotter, 1966). The instrument measures to what extent the individual considers that most of her life events are a consequence of chance or fate (External locus of control), or a consequence of personal decisions and effort (Internal locus of control).⁹

In 1980, the NLSY79 respondents also answered Rosenberg’s self-esteem instrument (Rosenberg, 1989). Self-esteem is a central component of self-concept. Rosenberg argued that the level of self-esteem was measurable and possible to compare across individuals. The self-esteem score is based on a 10-item questionnaire. Individuals with higher self-esteem have a higher score. Heckman, Stixrud, and Urzua (2006) combined elements from Rotter’s locus of control with Rosenberg’s self-esteem scale to construct a latent measure of non-cognitive skills. I will use standardized measures of both scales as controls in all wage equations to account for non-cognitive skills.

Occupational choices are coded using a 3-digit or 4-digit Census classification system. The 1970 Census Classification System was used between 1979 and 1993. The 1980 System was used between 1982 and 2000. Since 2002, all occupations have been classified using the 2000 Census codes. In the publicly available data for 2012, the occupation of 6,721 respondents who were active in the labor market were categorized into 424 occupational codes.

⁸I exclude 107 respondents who had some problem while taking the ASVAB. The math Z-score (variable R0648301) is based on Arithmetic Reasoning and Math Knowledge. The language Z-score (variable R0648305) is based on Word Knowledge and Paragraph Comprehension.

⁹The original Rotter locus of control score is coded in the external direction. I multiplied the score by -1 after standardization, to interpret the variable in the internal direction.

The occupation of the respondents' parents in 1978 was recorded using the 1970 Census Classification system. Each occupational code was merged to a corresponding O*Net math and language score using the crosswalks explained in Appendix A2. A missing value indicator was created in order to keep in the sample those respondents without parents or whose parents were out of the labor force.

The identification strategy uses occupational preferences as an instrument for occupational choices. In 1979, respondents were asked about their future plans regarding labor participation and occupational choice. The questionnaire starts by saying: *"Now I would like to talk with you about your future plans. What would you like to be doing when you are 35 years old?"*. The next question asked: *"What kind of work would you like to be doing when you are 35 years old?"*. The same set of questions was included again in the 1982 round. The answers to all these questions were coded using the 1970 Census Classifications system. I replaced each occupational code in the NLSY79 data with its corresponding math and language score from the O*Net database.

The key outcome of analysis is Hourly Rate of Pay, a measure constructed by the NLSY79 research team that combines wage or salary data with reported work time. For short, I will refer to Hourly Rate of Pay as wage. Only workers whose wage was at most \$150 were kept in the sample. I excluded self-employed individuals and workers who were employed in family business without pay. The sample was further restricted by the age of respondents in 1982. Since occupational aspirations are the basis for the instrumental variables, workers' labor market experience during young age should not drive the formation of such aspirations. Thus, only individuals who were 22 years of age or younger at the time of interview in 1982 were kept in the sample.

The empirical analysis focuses on labor market outcomes of the individuals in the sample between their the late twenties (1992) and late forties forties (2010). The selected sample size in 1992 is equal to 3,796 respondents, when their average age was equal to 29.7 years. The sample size in 2010 drops to 2,883 individuals, with an average age of 47.5 years. Summary

statistics for 1992, 2000 and 2010 are reported on Tables 2.2 through 2.4. Around half of the sample are women, 32 percent are African American and 19 percent are Hispanic. The current occupation O*Net scores (r_k^M, r_k^L) and the occupational aspirations scores (r_z^M, r_z^L) were standardized following the procedure described in Appendix A2 (Step 3).

2.3.3 Relative Math and Language Skills

It is possible to construct a measure of relative skills through the combination of O*Net and NLSY79 data. Let p_i^M and p_i^L be the individual math and language proficiency Z-scores available in the NLSY. A worker's proficiency should be compared to the average proficiency of other workers performing similar occupations. Since each occupation has an associated skill profile vector, it is possible to calculate a distance between any two occupations. This distance is used to defined which occupations are similar to one another.

The occupation chosen by worker i is denoted by $k(i)$. Recall that the math and language skill profile vector of occupation k is (r_k^M, r_k^L) . I define the average math and language skills of workers performing a similar occupation in the following way:

$$\bar{p}_{k(i),\epsilon}^M = \frac{\sum_j p_j^M}{N(j)} \quad \text{s.t.} \quad (r_{k(j)}^M - r_{k(i)}^M)^2 + (r_{k(j)}^L - r_{k(i)}^L)^2 \leq \epsilon^2 \quad (2.6)$$

$$\bar{p}_{k(i),\epsilon}^L = \frac{\sum_j p_j^L}{N(j)} \quad \text{s.t.} \quad (r_{k(j)}^M - r_{k(i)}^M)^2 + (r_{k(j)}^L - r_{k(i)}^L)^2 \leq \epsilon^2 \quad (2.7)$$

Two occupations are similar if the Euclidian distance between the corresponding skill profile vectors is less than or equal to ϵ . If worker i works in the same occupation as worker i' , then $k(i) = k(i')$. Furthermore, $\bar{p}_{k(i),\epsilon}^M = \bar{p}_{k(i'),\epsilon}^M$ and $\bar{p}_{k(i),\epsilon}^L = \bar{p}_{k(i'),\epsilon}^L$, because the set of individuals working in similar occupations is the same. The size of such set if equal to $N(j)$.

Consider the following example, represented in Figure 2.3. Suppose an individual works as a dishwasher. The green circle contains all the occupations similar to dishwashing if $\epsilon = 0.5$. In this case, $\bar{p}_{k=\text{Dishwashers},\epsilon=0.5}^M$ would be calculated as the average of individual math proficiency of those workers whose occupations are contained within the green circle.

In conclusion, relative math skills are defined as $p_i^M - \bar{p}_{k(i),\epsilon}^M$. Likewise, relative language skills are defined as $p_i^L - \bar{p}_{k(i),\epsilon}^L$. The value of ϵ is a critical assumption. As ϵ tends toward zero, the set of similar occupations shrinks and converges towards a singleton. The main regressions will be calculated for different values of ϵ as a robustness check.

2.4 Econometric Model

The main results from the occupational choice problem (Equations (2.4) and (2.5)) motivate an econometric model. The model should account for two different channels through which individual skills could generate a wage return. The first channel is *occupational sorting*: workers who are more proficient in a given skill might choose an occupation which has a higher skill content and earn higher wages. The second channel is *relative proficiency*: workers performing similar occupations might differ from one another in their individual skills and such differences might translate into different wages.

The following econometric model accounts for both channels and focuses on math (M) and language skills (L). To simplify the model's notation, let k stand for $k(i)$:

$$\ln(w_i) = \theta^w X_i + \alpha^M r_k^M + \alpha^L r_k^L + \beta^M (p_i^M - \bar{p}_{k,\epsilon}^M) + \beta^L (p_i^L - \bar{p}_{k,\epsilon}^L) + e_i \quad (2.8)$$

The dependent variable is the natural logarithm of hourly rate of pay. Vector X_i includes basic controls such as demographic characteristics, family background and non-cognitive

skills. Occupational choice is summarized by the skill profile vector (r_k^M, r_k^L) . Parameters α^M and α^L measure the wage return to occupational sorting. The wage return to relative math and language skills is captured by parameters β^M and β^L .

There are several reasons why the skill profile vector and relative skills are endogenous regressors. First of all, these variables are driven by occupational choice. The theoretical framework argued that occupational choices depend on the entire vector of individual skills and other unobservable characteristics such as the utility function over consumption (u) and the effort cost function (C) (See Equation (2.4)). Such sources of unobserved individual heterogeneity are embedded in the error term e_i .

Another reason to expect covariation between e_i and all the regressors in Equation (2.8), except for X_i , is the limited number of skills been analyzed. The econometric framework focuses on math and language skills, but occupations and workers are characterized by a larger set of skills, like dexterity or mechanical skills (Prada and Urzua, 2014). Occupational characteristics and individual skills other than math and language are omitted variables captured in the error term of the wage equation.

The wage equation has four endogenous variables. This paper proposes four instrumental variables based on occupational aspirations. Let $z(i)$ be the occupation to which worker i aspired and let z stand for $z(i)$. There is a skill profile vector (r_z^M, r_z^L) associated with occupational aspirations. It is derived from O*Net data using the appropriate crosswalks (See Appendix A2).

Most individuals in their 30s and 40s do not choose exactly the same occupation to which they aspire to back in their 20s, so usually $k \neq z$. However, this paper will demonstrate there is correlation between the skill content of occupational aspirations (r_z^M, r_z^L) and occupational choices (r_k^M, r_k^L) , which constitutes a key component of the identification strategy.

The four instrumental variables are:

1. r_z^M : the O*Net math z-score of the occupation to which the NLSY respondent aspired to back in 1982.
2. r_z^L : the equivalent O*Net z-score for the importance of language skills.
3. $p_i^M - \bar{p}_{z,\epsilon}^M$: relative individual math skills when each worker is compared to other workers who had similar occupational aspirations. $\bar{p}_{z,\epsilon}^M$ is the average math skills of respondents who aspired to occupation z and similar occupations. The occupations similar to occupation z are defined by the Euclidian distance of the corresponding skill profile vectors. The precise definition of $\bar{p}_{z,\epsilon}^M$ is the following:

$$\bar{p}_{z(i),\epsilon}^M = \frac{\sum_j p_j^M}{N(j)} \quad \text{s.t.} \quad (r_{z(j)}^M - r_{z(i)}^M)^2 + (r_{z(j)}^L - r_{z(i)}^L)^2 \leq \epsilon^2 \quad (2.9)$$

4. $p_i^L - \bar{p}_{z,\epsilon}^L$: relative language skills when compared to workers who had similar occupational aspirations. The definition of $\bar{p}_{z,\epsilon}^L$ is similar to Equation (2.9), but based on individual language proficiency (p_i^L) instead of math proficiency (p_i^M).

With four endogenous variables and four instruments, the system is just-identified. Equations (2.10) and (2.11) represent the first stage regressions for math and language skill content of occupational choices. Recall that k stands for $k(i)$ and z stands for $z(i)$:

$$r_k^M = \theta_k^M X_i + \gamma_M^M r_z^M + \gamma_L^M r_z^L + \delta_M^M (p_i^M - \bar{p}_{z,\epsilon}^M) + \delta_L^M (p_i^L - \bar{p}_{z,\epsilon}^L) + u_i^M \quad (2.10)$$

$$r_k^L = \theta_k^L X_i + \gamma_M^L r_z^M + \gamma_L^L r_z^L + \delta_M^L (p_i^M - \bar{p}_{z,\epsilon}^M) + \delta_L^L (p_i^L - \bar{p}_{z,\epsilon}^L) + u_i^L \quad (2.11)$$

2.5 Results

2.5.1 First stage regressions

The first stage regressions can be interpreted as statistical models of occupational choice. The dependent variables in Table 2.5 and Table 2.6 are elements of the skill profile vector (r_k^M, r_k^L) , which correspond to the occupation chosen by workers in three different years along their careers. The measurement units of r_k^M and r_k^L are standard deviations among the entire U.S. workforce of the O*Net importance score (See Section 2.3.1).

All regressions control for basic demographic characteristics. Family background controls are based on the skill profile vector of parents' occupation in 1978. Controls for non-cognitive skills are also included.¹⁰

The four instrumental variables are preceded by an asterisk in Tables 2.5 and 2.6. They are based on occupational aspirations declared by respondents in 1982: the skills profile vector of the desired occupation (r_z^M, r_z^L) and the relative math and language skills of the individual when compared to other respondents who had similar occupational aspirations $(p_i^M - \bar{p}_{z,\epsilon}^M, p_i^L - \bar{p}_{z,\epsilon}^L)$.

There is a positive correlation between the skill content of occupations held by respondents and their parents. This is the case for the O*Net math score (Table 2.5) as well as the O*Net language score (Table 2.6). The Rotter locus of control has no statistical association with occupational choices. On the other hand, self-esteem is a predictor of occupational choice along the language dimension. The coefficients on Rosenberg's self-esteem scale are positive and statistically significant when the dependent variable is the O*Net language score of workers' current occupation (Table 2.6).

¹⁰The coefficients for age and the missing value indicators are not reported in Tables 2.5 and 2.6. The complete regression results for every year of available data between 1992 and 2012 can be found in Appendix A4.

For the majority of individuals, the occupation they would like to reach is not the same occupation they actually obtained many years later: only 9 percent of the sample if 1996 worked exactly in the same occupation to which they aspired to back in 1982. Despite this, the first stage regressions show evidence of correlation in the skill content of occupational choices and aspirations. The O*Net math and language scores which correspond to occupational aspirations in 1982 (r_z^M, r_z^L) have positive and significant coefficients in all regressions presented in Tables 2.5 and 2.6.

Relative skills also matter for occupational sorting. Individuals who were more able in math, when compared to other individuals who had similar occupational aspirations, sort themselves into occupations with a higher skill content. This conclusion is derived from the sign and statistical significance of the coefficient associated with regressor $p_i^M - \bar{p}_{z,\epsilon}^M$ in both first stage regressions. Relative language skills matter only for the occupational sorting of workers along the language dimension.

The statistical models of occupational choice do a better job at explaining the sorting of workers along the language skill dimension of occupations (Table 2.6), when compared to sorting along the math dimension (Table 2.5). The R^2 of the first stage regressions which attempt to explain the math skill content of occupational choices (r_k^M) is between 0.07 and 0.10, depending on the year. The same statistic for the models for which the O*Net language score (r_k^L) is the dependent variable is around 0.23.

Both tables also report the F statistics. All F statistics for those models in which the dependent variable is the language skill score of occupational choices are above 70. In the case of math skills, the lowest F statistics is 18, for the regression in the year 2010. The regressions and statistics for all years of data between 1992 and 2012 are available in Appendix A4. Overall, the four instrumental variables have enough predictive power of the endogenous regressors to discard a possible weak instruments problem.

2.5.2 OLS and IV models

The regression of interest is a wage equation which accounts for occupational sorting and relative skills (Equation 2.8). Occupational sorting is accounted for by the O*Net math and language scores of the current occupation (r_k^M and r_k^L). Thus, the wage return to occupational sorting is measured by the estimates of parameters α^M and α^L . The estimates of parameters β^M and β^L capture the wage return to relative math and language skills. Recall that relative skills depend on the set of similar occupations used to calculate the average skill of related workers and the set of similar occupations is determined by ϵ (see Section 2.3.3). In the main results that follow, $\epsilon = 0.25$ standard deviations. I will also discuss results obtained using other values of ϵ as a robustness check.

The first three columns of Table 2.7 summarize the OLS estimates of the wage equation when individuals in the sample were on average in their late twenties (1992), late thirties (2000) and late forties (2010). The first four rows report the point estimates and heteroskedasticity-robust standard errors of α^M , α^L , β^M and β^L . The last three columns in the same table report the 2SLS estimates.¹¹

OLS underestimates the return to occupational sorting, when compared to the 2SLS estimates. For example, the OLS estimate of α^M for the year 2000 is equal to 0.103, with a standard error of 0.01. The equivalent 2SLS estimate is 0.481, with a standard error of 0.136. This pattern in the results holds for all the other years analyzed. On the other hand, the return to relative skills is overestimated by OLS regressions. The 2SLS point estimates of β^M and β^L are positive but only statistically significant at a 10% level in 1992.

According to the 2SLS regressions in Table 2.7, there is a positive wage return to occupational sorting ($\alpha^M > 0, \alpha^L > 0$), but there is no evidence of a wage return on relative proficiency (I can't reject $\beta^M = 0, \beta^L = 0$). There is an important economic interpretation

¹¹There are four first stage regression tables behind the 2SLS estimates. The regression tables for endogenous variables r_k^M and r_k^L can be found in Tables 2.5 and 2.6. The first stage regressions for relative skills are available in Appendix A3. Regressions results for all the years are in Appendix A4.

of these results: worker's skills can only be translated into higher wages through better occupational matches.

Consider the following example. Table 2.1 presents the skill profile vector (r_k^M, r_k^L) of two occupations in the health industry (diagnostic technicians and registered nurses). It also contains the average individual skills of workers in related occupations $(\bar{p}_{k,\epsilon}^M, \bar{p}_{k,\epsilon}^L)$, when $\epsilon = 0.25$. Suppose a worker holds a job as a diagnostic technician. Furthermore, the worker is average when compared to other workers in similar occupations. Therefore, $p_i^M = \bar{p}_{k,\epsilon}^M = 0.07$ and $p_i^L = \bar{p}_{k,\epsilon}^L = 0.19$.

Suppose this worker would like to change her job and become a registered nurse. The worker should become more proficient in both math and language skills in order to maintain her status as an average worker, because $\bar{p}_{k,\epsilon}^M$ and $\bar{p}_{k,\epsilon}^L$ are slightly higher for registered nurses. However, this accumulation of skills might not translate into higher wage returns, not only because $\beta^M = \beta^L = 0$, but also because relative skills are kept constant. Once the worker finds a new job as a registered nurse, the wage returns are realized. Using the 2010 2SLS estimates from Table 2.7, the model predicts an increase in the hourly rate of pay of approximately 15.3% or 0.142 log points ($= \alpha^M * \Delta r_k^M + \alpha^L * \Delta r_k^L = 0.494 * 0.15 + 0.426 * 0.16$).

The main regression results are robust to changes in the value of ϵ . All results presented so far use $\epsilon = 0.25$ to define the set of similar occupations. As ϵ becomes smaller, the set of similar occupations shrinks. The remaining occupations are much closer to one another, but the number of workers used to calculate average skills also drops. Tables 2.8 and 2.9 present the OLS and 2SLS regressions based on alternative values for ϵ (0.50 and 0.15). There are no substantial changes in the main pattern of results.

2.6 Concluding Remarks

This paper has shown the value of extracting information from occupational choices. The endogeneity of occupations in wage equations can be overcome if occupational aspirations are used to instrument occupational choices. In order to do so, occupations must be defined and measured in terms of the skill profile they required. The O*Net is a valuable research tool that quantifies different dimensions of occupations.

This paper has focused on two possible mechanisms through which skills might have an effect on wages: *occupational sorting* and *relative proficiency*. It is possible to account for both mechanisms in a unified econometric framework. I found evidence of positive and persistent wage returns to occupational sorting, but no evidence of a return to relative proficiency. Pre-market skills are good predictors of wages through the life cycle (Neal and Johnson, 1996; Heckman, Stixrud, and Urzua, 2006) because they play a fundamental role in occupational sorting.

The estimation of the wage return to skills is relevant, not only for an accurate description of labor markets, but also for the proper design of active labor market policies (Heckman, LaLonde, and Smith, 1999). The appropriate design of job training programs should take into account the importance of occupational sorting. Suppose a public job training program has the purpose of enhancing workers' skills, but the program does not help trainees in the process of finding new jobs in which the new set of skills are relevant. If workers return to the labor market without a significant occupational transition, then most likely there will be no wage return of intervention.

	Occ. code	r_k^M	r_k^L	$\bar{p}_{k,\epsilon}^M$	$\bar{p}_{k,\epsilon}^L$
Diagnostic Technician (A)	3320	0.52	0.86	0.07	0.19
Registered Nurses (B)	3130	0.67	1.02	0.16	0.24
Differences, Δ (B - A)		0.15	0.16	0.09	0.05

Table 2.1: An example: skill content and average skills for two occupations

Table 2.2: Summary Statistics, 1992

Variable	Mean	Std. Dev.	Min.	Max.	N
Ln of Hourly Rate of Pay	2.22	0.51	0	5.01	3796
Age (years)	29.88	1.61	27	33	3796
Female indicator	0.48	.	0	1	3796
African American indicator	0.31	.	0	1	3796
Hispanic indicator	0.19	.	0	1	3796
Mother's Occupation in 1978: Math O*Net score	-0.21	0.78	-2.86	2.25	3796
Father's Occupation in 1978: Math O*Net score	0.1	0.85	-2.86	2.99	3796
Mother's Occupation in 1978: Language O*Net score	-0.05	0.72	-2.22	2.36	3796
Father's Occupation in 1978: Language O*Net score	-0.22	0.81	-2.54	2.28	3796
Mother's Occupation in 1978: Missing ind.	0.41	.	0	1	3796
Father's Occupation in 1978: Missing ind.	0.27	.	0	1	3796
Rotter Locus of Control, 1979 (Z Score)	-0.05	0.97	-3.03	1.92	3796
Rosenberg Self-Esteem, 1980 (Z Score)	-0.03	0.97	-3.72	1.85	3796
→ Current Occupation: Math O*Net score	0.05	0.97	-2.86	2.25	3796
→ Current Occupation: Language O*Net score	-0.03	0.96	-2.54	2.48	3796

Continued on next page...

... table 2.2 continued

	Variable	Mean	Std. Dev.	Min.	Max.	N
→	Relative Math Skills, Current Occupation	$p_i^M - \bar{p}_{k,\epsilon}^M$	0.88	-3.63	3.38	3796
→	Relative Language Skills, Current Occupation	$p_i^L - \bar{p}_{k,\epsilon}^L$	0.9	-2.67	3.48	3796
*	Occupational Aspiration in 1982: Math O*Net score	r_z^M	0.32	-2.36	2.99	3796
*	Occupational Aspiration in 1982: Language O*Net score	r_z^L	0.39	-2.19	2.28	3796
*	Relative Math Skills, Occupational Aspiration in 1982	$p_i^M - \bar{p}_{z,\epsilon}^M$	0.92	-2.98	3.04	3796
*	Relative Language Skills, Occupational Aspiration in 1982	$p_i^L - \bar{p}_{z,\epsilon}^L$	0.93	-3.38	3.46	3796

Endogenous variables are preceded by an arrow (→). Instrumental variables are preceded by an asterisk (*).

Similar occupations are defined using a radius of 0.25 standard deviations ($\epsilon = 0.25$).

Table 2.3: Summary Statistics, 2000

Variable	Mean	Std. Dev.	Min.	Max.	N
Ln of Hourly Rate of Pay	2.6	0.58	0.04	4.79	3549
Age (years)	37.92	1.64	35	41	3549
Female indicator	0.5	.	0	1	3549
African American indicator	0.32	.	0	1	3549
Hispanic indicator	0.19	.	0	1	3549
Mother's Occupation in 1978: Math O*Net score	-0.21	0.78	-2.86	2.25	3549
Father's Occupation in 1978: Math O*Net score	0.07	0.83	-2.86	2.99	3549
Mother's Occupation in 1978: Language O*Net score	-0.06	0.72	-2.22	2.23	3549
Father's Occupation in 1978: Language O*Net score	-0.23	0.8	-2.54	2.28	3549
Mother's Occupation in 1978: Missing ind.	0.41	.	0	1	3549
Father's Occupation in 1978: Missing ind.	0.29	.	0	1	3549
Rotter Locus of Control, 1979 (Z Score)	-0.07	0.98	-3.03	1.92	3549
Rosenberg Self-Esteem, 1980 (Z Score)	-0.05	0.96	-3.72	1.85	3549
→ Current Occupation: Math O*Net score	0.12	0.99	-2.86	2.89	3549
→ Current Occupation: Language O*Net score	0.01	0.95	-2.54	2.48	3549

Continued on next page...

... table 2.3 continued

	Variable	Mean	Std. Dev.	Min.	Max.	N
→	Relative Math Skills, Current Occupation	$p_i^M - \bar{p}_{k,\epsilon}^M$	0.87	-2.83	3.33	3549
→	Relative Language Skills, Current Occupation	$p_i^L - \bar{p}_{k,\epsilon}^L$	0.88	-2.7	3.2	3549
*	Occupational Aspiration in 1982: Math O*Net score	r_z^M	0.91	-2.67	2.99	3549
*	Occupational Aspiration in 1982: Language O*Net score	r_z^L	0.8	-2.44	2.28	3549
*	Relative Math Skills, Occupational Aspiration in 1982	$p_i^M - \bar{p}_{z,\epsilon}^M$	0.92	-2.98	3.04	3549
*	Relative Language Skills, Occupational Aspiration in 1982	$p_i^L - \bar{p}_{z,\epsilon}^L$	0.93	-3.38	3.46	3549

Endogenous variables are preceded by an arrow (→). Instrumental variables are preceded by an asterisk (*).

Similar occupations are defined using a radius of 0.25 standard deviations ($\epsilon = 0.25$).

Table 2.4: Summary Statistics, 2010

Variable	Mean	Std. Dev.	Min.	Max.	N
Ln of Hourly Rate of Pay	2.88	0.59	0.36	4.97	2883
Age (years)	47.52	1.61	45	51	2883
Female indicator	0.52	.	0	1	2883
African American indicator	0.32	.	0	1	2883
Hispanic indicator	0.19	.	0	1	2883
Mother's Occupation in 1978: Math O*Net score	-0.22	0.78	-2.86	2.25	2883
Father's Occupation in 1978: Math O*Net score	0.07	0.82	-2.86	2.99	2883
Mother's Occupation in 1978: Language O*Net score	-0.05	0.72	-2.22	2.36	2883
Father's Occupation in 1978: Language O*Net score	-0.23	0.8	-2.54	2.28	2883
Mother's Occupation in 1978: Missing ind.	0.41	.	0	1	2883
Father's Occupation in 1978: Missing ind.	0.29	.	0	1	2883
Rotter Locus of Control, 1979 (Z Score)	-0.11	0.98	-3.03	1.92	2883
Rosenberg Self-Esteem, 1980 (Z Score)	-0.06	0.95	-3.72	1.85	2883
→ Current Occupation: Math O*Net score	0.03	0.95	-2.86	2.25	2883
→ Current Occupation: Language O*Net score	0.06	0.97	-2.57	2.56	2883

Continued on next page...

... table 2.4 continued

	Variable	Mean	Std. Dev.	Min.	Max.	N
→	Relative Math Skills, Current Occupation	$p_i^M - \bar{p}_{k,\epsilon}^M$	0.9	-2.84	3.21	2883
→	Relative Language Skills, Current Occupation	$p_i^L - \bar{p}_{k,\epsilon}^L$	0.88	-2.77	3.28	2883
*	Occupational Aspiration in 1982: Math O*Net score	r_z^M	0.9	-2.3	2.99	2883
*	Occupational Aspiration in 1982: Language O*Net score	r_z^L	0.78	-2.16	2.28	2883
*	Relative Math Skills, Occupational Aspiration in 1982	$p_i^M - \bar{p}_{z,\epsilon}^M$	0.93	-2.98	3.22	2883
*	Relative Language Skills, Occupational Aspiration in 1982	$p_i^L - \bar{p}_{z,\epsilon}^L$	0.92	-3.38	3.46	2883

Endogenous variables are preceded by an arrow (→). Instrumental variables are preceded by an asterisk (*).

Similar occupations are defined using a radius of 0.25 standard deviations ($\epsilon = 0.25$).

Table 2.5: First Stage - Current Occupation O*Net Score: Math (r_k^M)

	1992	2000	2010
Female indicator	-0.024 (0.032)	-0.105*** (0.033)	-0.050 (0.036)
African American indicator	-0.092** (0.042)	-0.170*** (0.044)	-0.159*** (0.046)
Hispanic indicator	0.024 (0.043)	-0.038 (0.045)	0.005 (0.050)
Mother's Occupation in 1978: Math O*Net score	0.058** (0.023)	0.044* (0.024)	-0.026 (0.027)
Father's Occupation in 1978: Math O*Net score	0.027 (0.020)	0.047** (0.020)	0.075*** (0.023)
Mother's Occupation in 1978: Language O*Net score	-0.011 (0.025)	-0.009 (0.027)	0.049 (0.030)
Father's Occupation in 1978: Language O*Net score	0.021 (0.022)	0.012 (0.022)	-0.004 (0.024)
Rotter Locus of Control, 1979 (Z Score)	-0.001 (0.017)	0.027 (0.017)	0.013 (0.019)
Rosenberg Self-Esteem, 1980 (Z Score)	0.047*** (0.017)	0.044** (0.018)	0.021 (0.019)
* Occupational Aspiration in 1982: Math O*Net score (r_z^M)	0.152*** (0.018)	0.129*** (0.018)	0.129*** (0.020)
* Occupational Aspiration in 1982: Language O*Net score (r_z^L)	0.058*** (0.020)	0.096*** (0.021)	0.054** (0.023)
* Relative Math Skills, Occ. Aspiration in 1982 ($p_i^M - \bar{p}_{z,\epsilon}^M$)	0.162*** (0.027)	0.211*** (0.027)	0.127*** (0.030)
* Relative Language Skills, Occ. Aspiration in 1982 ($p_i^L - \bar{p}_{z,\epsilon}^L$)	0.016 (0.027)	-0.025 (0.027)	0.009 (0.029)

Constant	0.310 (0.291)	0.928** (0.383)	0.716 (0.528)
----------	------------------	--------------------	------------------

R^2	0.08	0.10	0.07
F statistic	37.419	38.764	18.082
Observations	3796	3549	2883

Heteroskedasticity-robust s.e in parentheses. Instrumental variables are preceded by an asterisk (*).

Additional controls: age and missing value indicators for parent's occ. in 1978. $\epsilon = 0.25$

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6: First Stage - Current Occupation O*Net Score: Language (r_k^L)

	1992	2000	2010
Female indicator	0.420*** (0.030)	0.462*** (0.030)	0.532*** (0.034)
African American indicator	0.060 (0.038)	0.032 (0.039)	0.008 (0.043)
Hispanic indicator	0.118*** (0.039)	0.189*** (0.039)	0.164*** (0.045)
Mother's Occupation in 1978: Math O*Net score	0.049** (0.022)	0.008 (0.022)	0.033 (0.025)
Father's Occupation in 1978: Math O*Net score	0.011 (0.018)	0.029 (0.018)	0.037* (0.022)
Mother's Occupation in 1978: Language O*Net score	0.023 (0.024)	0.077*** (0.024)	0.052* (0.027)
Father's Occupation in 1978: Language O*Net score	0.063*** (0.020)	0.052*** (0.020)	0.084*** (0.022)
Rotter Locus of Control, 1979 (Z Score)	0.013 (0.015)	-0.003 (0.015)	0.022 (0.018)
Rosenberg Self-Esteem, 1980 (Z Score)	0.057*** (0.016)	0.078*** (0.016)	0.041** (0.018)
* Occupational Aspiration in 1982: Math O*Net score (r_z^M)	0.035** (0.016)	0.051*** (0.016)	0.038** (0.018)
* Occupational Aspiration in 1982: Language O*Net score (r_z^L)	0.247*** (0.019)	0.244*** (0.019)	0.249*** (0.022)
* Relative Math Skills, Occ. Aspiration in 1982 ($p_i^M - \bar{p}_{z,\epsilon}^M$)	0.150*** (0.024)	0.121*** (0.025)	0.155*** (0.028)
* Relative Language Skills, Occ. Aspiration in 1982 ($p_i^L - \bar{p}_{z,\epsilon}^L$)	0.111*** (0.023)	0.160*** (0.025)	0.124*** (0.028)

Constant	0.214 (0.271)	0.266 (0.337)	0.030 (0.486)
R^2	0.21	0.23	0.24
F statistic	81.522	89.676	74.012
Observations	3796	3549	2883

Heteroskedasticity-robust s.e in parentheses. Instrumental variables are preceded by an asterisk (*).

Additional controls: age and missing value indicators for parent's occ. in 1978. $\epsilon = 0.25$

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7: OLS and IV models - Ln of Hourly Rate of Pay ($\epsilon = 0.25$)

	OLS			IV		
	1992	2000	2010	1992	2000	2010
→ Current Occupation: Math O*Net score (r_k^M)	0.069*** (0.008)	0.103*** (0.010)	0.096*** (0.011)	0.327*** (0.076)	0.481*** (0.136)	0.494*** (0.153)
→ Current Occupation: Language O*Net score (r_k^L)	0.121*** (0.008)	0.137*** (0.010)	0.172*** (0.011)	0.158*** (0.060)	0.259*** (0.096)	0.426*** (0.105)
→ Relative Math Skills, Current Occ. ($p_i^M - \bar{p}_{k,\epsilon=0.25}^M$)	0.080*** (0.012)	0.106*** (0.015)	0.128*** (0.016)	0.043* (0.025)	0.019 (0.038)	0.030 (0.040)
→ Relative Language Skills, Current Occ. ($p_i^L - \bar{p}_{k,\epsilon=0.25}^L$)	0.026** (0.013)	0.036** (0.015)	0.028 (0.018)	0.029* (0.017)	0.047 (0.029)	-0.001 (0.031)
Rotter Locus of Control, 1979 (Z Score)	0.021*** (0.008)	0.030*** (0.009)	0.023** (0.010)	0.016* (0.009)	0.013 (0.012)	0.009 (0.016)
Rosenberg Self-Esteem, 1980 (Z Score)	0.068*** (0.008)	0.065*** (0.010)	0.060*** (0.011)	0.044*** (0.011)	0.022 (0.015)	0.030* (0.017)
Constant	1.928***	2.823***	2.889***	1.773***	2.294***	2.435***

	(0.134)	(0.198)	(0.289)	(0.161)	(0.292)	(0.434)
Average age (years)	29.9	37.9	47.5	29.9	37.9	47.5
Observations	3796	3549	2883	3796	3549	2883

Heteroskedasticity-robust s.e in parentheses. Endogenous variables are preceded by an arrow (\rightarrow).

Additional controls: age in years, Female, African American and Hispanic indicators.

Additional controls: Mother's and Father's occupations in 1978 (O*Net math and language scores, and missing value indicators).

Similar occupations are defined using a radius of 0.25 standard deviations ($\epsilon = 0.25$).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.8: OLS and IV models - Ln of Hourly Rate of Pay ($\epsilon = 0.50$)

	OLS			IV		
	1992	2000	2010	1992	2000	2010
→ Current Occupation: Math O*Net score (r_k^M)	0.072*** (0.008)	0.109*** (0.009)	0.100*** (0.011)	0.324*** (0.076)	0.473*** (0.135)	0.488*** (0.153)
→ Current Occupation: Language O*Net score (r_k^L)	0.123*** (0.008)	0.140*** (0.010)	0.172*** (0.011)	0.152** (0.060)	0.255*** (0.096)	0.423*** (0.108)
→ Relative Math Skills, Current Occ. ($p_i^M - \bar{p}_{k,\epsilon=0.50}^M$)	0.090*** (0.012)	0.123*** (0.014)	0.141*** (0.016)	0.045* (0.025)	0.023 (0.037)	0.036 (0.040)
→ Relative Language Skills, Current Occ. ($p_i^L - \bar{p}_{k,\epsilon=0.50}^L$)	0.033*** (0.013)	0.050*** (0.015)	0.040** (0.018)	0.033* (0.017)	0.045 (0.028)	-0.005 (0.031)
Rotter Locus of Control, 1979 (Z Score)	0.018** (0.008)	0.025*** (0.009)	0.020* (0.010)	0.016* (0.009)	0.013 (0.012)	0.009 (0.015)
Rosenberg Self-Esteem, 1980 (Z Score)	0.064*** (0.008)	0.057*** (0.010)	0.055*** (0.011)	0.044*** (0.011)	0.022 (0.015)	0.030* (0.016)
Constant	1.901***	2.764***	2.837***	1.773***	2.301***	2.437***

	(0.133)	(0.196)	(0.287)	(0.160)	(0.289)	(0.431)
Average age (years)	29.9	37.9	47.5	29.9	37.9	47.5
Observations	3796	3549	2883	3796	3549	2883

Heteroskedasticity-robust s.e in parentheses. Endogenous variables are preceded by an arrow (\rightarrow).

Additional controls: age in years, Female, African American and Hispanic indicators.

Additional controls: Mother's and Father's occupations in 1978 (O*Net math and language scores, and missing value indicators).

Similar occupations are defined using a radius of 0.50 standard deviations ($\epsilon = 0.50$).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.9: OLS and IV models - Ln of Hourly Rate of Pay ($\epsilon = 0.15$)

	OLS			IV		
	1992	2000	2010	1992	2000	2010
→ Current Occupation: Math O*Net score (r_k^M)	0.067*** (0.008)	0.100*** (0.010)	0.094*** (0.011)	0.329*** (0.077)	0.483*** (0.136)	0.490*** (0.149)
→ Current Occupation: Language O*Net score (r_k^L)	0.121*** (0.008)	0.136*** (0.010)	0.167*** (0.011)	0.166*** (0.059)	0.264*** (0.095)	0.426*** (0.104)
→ Relative Math Skills, Current Occ. ($p_i^M - \bar{p}_{k,\epsilon=0.15}^M$)	0.072*** (0.013)	0.088*** (0.015)	0.109*** (0.017)	0.038 (0.026)	0.016 (0.039)	0.037 (0.040)
→ Relative Language Skills, Current Occ. ($p_i^L - \bar{p}_{k,\epsilon=0.15}^L$)	0.020 (0.013)	0.032** (0.015)	0.015 (0.018)	0.027 (0.018)	0.046 (0.029)	-0.003 (0.031)
Rotter Locus of Control, 1979 (Z Score)	0.023*** (0.008)	0.033*** (0.009)	0.027*** (0.010)	0.017* (0.009)	0.014 (0.012)	0.009 (0.016)
Rosenberg Self-Esteem, 1980 (Z Score)	0.071*** (0.008)	0.070*** (0.010)	0.067*** (0.011)	0.045*** (0.011)	0.022 (0.015)	0.030* (0.017)
Constant	1.959***	2.882***	2.948***	1.782***	2.304***	2.431***

	(0.134)	(0.198)	(0.291)	(0.163)	(0.296)	(0.433)
Average age (years)	29.9	37.9	47.5	29.9	37.9	47.5
Observations	3796	3549	2883	3796	3549	2883

Heteroskedasticity-robust s.e in parentheses. Endogenous variables are preceded by an arrow (\rightarrow).

Additional controls: age in years, Female, African American and Hispanic indicators.

Additional controls: Mother's and Father's occupations in 1978 (O*Net math and language scores, and missing value indicators).

Similar occupations are defined using a radius of 0.15 standard deviations ($\epsilon = 0.15$).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 3

Gender differences in occupational aspirations, occupational choices and returns to skills: evidence from the Philippines (CLHNS)

3.1 Introduction

Skill formation plays a key role in economic development ([Hanushek and Woessmann, 2008](#)). The build-up of productive skills among the population is one of different mechanisms through which human capital is accumulated in an economy. Unfortunately, results in international standardized tests, such as PISA or TIMSS, demonstrate the existence of large skill gaps between developed and developing countries ([OECD, 2011](#); [Mullis et al., 2012](#)).

Another difference between labor markets in developed and developing countries is the

portfolio of available occupations (Banerjee and Newman, 1993). Some skill-intensive and very specialized occupations that a worker could aspire to in a country like the United States are not always a feasible option in poorer countries. At the same time, the relative importance of some occupations and the economic return to different skills could change with time, depending on each country's stage of economic development.

I consider that economic development can be analyzed through the lens of occupational choice since occupations carry substantial information about the human capital of workers. The previous chapter of this dissertation used the skill content of occupations to study the return to occupational sorting and relative skills in the United States. The identification strategy was based on the correlation between the skill content of occupational choices and occupational aspirations.

This chapter explores the validity of using the same identification strategy in the context of a developing country. I will use data from the Cebu Longitudinal Health and Nutrition Survey (CLHNS) from the Philippines, because respondents were asked about their occupational aspirations during adolescence and occupational choices in their early twenties.

The Occupational Information Network (O*Net) was a valid data source of the skill content of occupations in the United States, but there is no equivalent data source for the Philippines or any other developing country. This chapter proposes a cost-effective mechanism to collect similar data, following the protocols used in the United States as close as possible (Tsacoumis and Willison, 2010). I surveyed ten psychologists from the Philippines and hired their services to analyze 292 Filipino occupations on five dimensions: reading, writing, speaking, math and educational requirements. This novel data is used to score occupational choices and occupational aspirations within the CLHNS data.¹

The rest of this chapter is organized as follows: Section 3.2 presents a literature re-

¹The data collection process was possible thanks to a \$1,000 grant provided by the Center for International Food and Agriculture Policy (CIFAP) at the University of Minnesota. I had extraordinary support from Jennifer Andrea Valbuena Fajardo as my research assistant during the data collection process.

view. Section 3.3 summarizes the main traits of the CLHNS. Section 3.4 explains the data collection process from Filipino psychologists. Section 3.5 explains the econometric framework and the regressions results are analyzed in Section 3.6. The main conclusions and a discussion of the results are available in Section 3.7.

3.2 Literature Review

Sociologists have long recognized the usefulness of occupations to derive measures of sociological concepts, such as class, prestige or socioeconomic status (Burgard, 2008). Survey respondents are less reluctant to declare their occupational status, as compared to information about their assets or income. Furthermore, occupational status is widely available in censuses and household surveys around the world. Sociologists have tested different theories of social stratification through empirical studies based on occupational status. For example, Duncan (1961) proposed a ranking system of occupations for the United States, based on occupational prestige and its relation to income and educational requirements. This index is known as the Duncan Socioeconomic Index (SEI). Blau and Duncan (1967) used the Duncan SEI to study social mobility, career paths and the intergenerational dynamics of occupational choice. A comprehensive review of related sociological studies can be found in Hauser and Warren (1997).

The empirical study of occupational prestige began in the United States with a study by the National Opinion Research Center (North and Hatt, 1947). During the early 1950s, similar studies were done in other developed countries around the world.² Edward Tiryakian, as a graduate student of Sociology at Harvard at that time, carried out the first study of occupational prestige in a developing country: the Philippines. Tiryakian (1958) interviewed 641 Filipinos between 1954 and 1955 in the island of Luzon, where the capital city of Manila is located. Respondents were asked to rank 30 occupations according to their social

²See Tiryakian (1958, p. 1) for a list of the early studies of occupational prestige around the world.

standing. Barber, engineer, lawyer and physician were among the occupations included in the survey. [Tiryakian \(1958\)](#) reported the ranking of occupations according to their prestige and found a high correlation with previous rankings from developed countries: professional groups were ranked the highest and unskilled occupations were ranked the lowest. Further research has concluded that "occupational prestige measures [...] have shown high consensus among individuals from different social positions, across societal contexts, and over time." ([Burgard, 2008](#), p. 26)

Tiryakian also collected data on job satisfaction and occupational aspirations within the same sample of 641 Filipino workers. He published his results in [Tiryakian \(1959\)](#). Respondents were asked if they would like to keep working in the same occupation they currently had or change it. Around 25% of workers would not change their current occupation and white-collar work was the preferred option among the remaining 75%.

Occupational aspirations for future generations were measured by [Tiryakian \(1959\)](#) using the following question: "*What occupation would you advise your children to enter, assuming they had the chance to do so?*" (p. 436). The author found that at least a third of respondents would like their children to work in a professional occupation, a fact consistent with the high prestige of professional occupations among the Filipino sample. The proportion was even higher among parents with a white-collar occupation.

Since the pioneer work of Edward Tiryakian, there has been little research on occupational aspirations and choices in the Philippines: a subsequent study by [Voth \(1970\)](#) published an alternative occupational prestige index for 148 occupations; [Bacol \(1971\)](#) used the National Demographic Survey of 1968 to study intergenerational occupational mobility, by calculating a socioeconomic index based on the methodology of the Duncan SEI; and [Voth \(1971\)](#) focused on the prestige of farming among Filipino workers.

Besides lack of data, a reason for the limited number of recent studies could be the critique of composite occupational indexes postulated by [Hauser and Warren \(1997\)](#) in the

mid 1990s:

”If there is any general conclusion to be drawn from the present analysis, it is that we ought to move toward a more specific and disaggregated appraisal of the effects of occupational characteristics on social, psychological, economic, political, and health outcomes. While composite measures of occupational status may have heuristic uses, the global concept of occupational status is scientifically obsolete.” (p. 251)

I take into account Hauser and Warren’s critique and focus on the disaggregated skill content of occupations.

Studies on the career effects of occupational aspirations require longitudinal data. The Cebu Longitudinal Health and Nutrition Survey (CLHNS) followed a cohort of individuals born in the metropolitan area of Cebu City (Central Visayas, Philippines) since the mid 1980s. Research based on the CLHNS evolved as the cohort aged. Good summaries of the research derived from CLHNS data can be found in [Feranil, Gultiano, and Adair \(2008\)](#) and [Adair et al. \(2011\)](#).

The first studies focused on the patterns of prenatal care ([Wong et al., 1987](#)). Subsequent studies explored the determinants of infant health status and estimated the production function of early health outcomes, such as diarrhea, febrile respiratory infections and growth ([Cebu Study Team, 1991, 1992](#)). [Cebu Study Team \(1992\)](#) was the first paper based on CLHNS data to account for endogeneity of household choices.

Cognitive development and academic achievement were measured in the first and second follow-up rounds (1991 and 1994). [Mendez and Adair \(1999\)](#) explored the consequences of stunting at early age on cognitive development. The authors found a negative association of severe stunting at age 2 with IQ by age 11. The study by Mendez and Adair presented correlation but no causal evidence. [Glewwe and King \(2001\)](#) were the first authors to present

causal evidence on the effect of nutritional status on cognitive development using CLHNS data. Glewwe and King used an instrumental variables approach: they instrumented children's growth with measures of rainfall, local food prices and mother's physiological characteristics. In a subsequent paper, [Glewwe, Jacoby, and King \(2001\)](#) studied the causal effect of early nutrition on academic achievement. The authors found a positive effect of early nutritional status on the performance in math and reading tests by age 11. Their identification strategy combined a first-difference model across siblings with two-stage least squares.³

By the mid 2000's, participants in the CLHNS were in their early twenties and had begun to acquire work experience. A last group of recent papers has studied the determinants of labor market outcomes within the CLHNS. [Carba, Tan, and Adair \(2009\)](#) was the first study to measure the association between length-for-age at age 2 and work status by early adulthood. The authors found a negative correlation between early childhood growth problems and the probability of employment in the formal sector by age 20. [Avgeropoulou \(2014\)](#) focused on the impact of early health status on wages, using the same identification strategy proposed by [Glewwe and King \(2001\)](#), and [Carvalho \(2012\)](#) analyzed which early childhood conditions determine the intergenerational transmission of socioeconomic status.

To the best of my knowledge, no study has explored the relationship between occupational aspirations and occupational choices using the CLHNS. The closest paper is that of [Lee and Adair \(2011\)](#), which found evidence of occupational gender segregation using a sample of 924 respondents from the CLHNS. Lee and Adair found that young working Filipino women are concentrated in occupations which do not require heavy physical exertion. The authors focused on occupational choices in 2005 (the fifth follow-up survey), but did not establish the connection with occupational aspirations declared back in 1998 (the third follow-up survey). This paper attempts to fill this void in the literature.

³A recent study by [Peet et al. \(2015\)](#) measured the association between height-for-age and cognitive development in three different samples from Finland, the United Kingdom and the Philippines. Data for the Philippines were from the CLHNS.

3.3 Cebu Longitudinal Health and Nutrition Survey (CLHNS)

The main goal of the CLHNS was to study the relation between prenatal and postnatal nutritional conditions on a child's health status in the short run and in the long run. The study began in 1983. A random sample of 3,327 pregnant women were selected in the Province of Cebu, Philippines. All women gave birth between May 1983 and April 1984. Baseline information was collected during the last months of pregnancy, at birth, and every two months during the first two years of the child's life. Since then, there have been a total of seven follow-up interviews: 1991, 1994, 1998, 2002, 2005, 2007 and 2009 (Feranil, Gultiano, and Adair, 2008; Adair et al., 2011).⁴

Table 3.1 summarizes all the waves in the study. Data for 2,260 children were collected during the first follow-up and subsequent surveys have tried to keep track of them. The questions used in each follow-up take into account the aging and maturing process of mothers and their children. For example, information about school entry was collected during the first follow-up (1991), adolescent sexual behavior was considered during the third follow-up (1998) and schooling outcomes as well as labor market information was collected during the fourth follow-up (2002). Mothers were surveyed in every follow-up up until 2007, and data about community characteristics were gathered up until 2005.

Like the NLSY79, the CLHNS has a direct measure of math and language skills before individuals entered the labor market, although at a younger age. A math test composed of 60 questions was answered by all children during the second follow-up (1994), which implies that respondents were between 10 and 12 years old at the time of testing. Reading tests in Cebuano and English were administered during the same follow-up. These variables were

⁴The CLHNS data and documentation are available at <http://www.cpc.unc.edu/projects/cebu>. I analyzed the documentation and codebooks of four longitudinal studies carried out in developing countries to determine which one was the most appropriate for my dissertation: 1) the Indonesian Family Life Survey (IFLS), 2) the Mexican Family Life Survey (MxFLS), 3) the Colombian Longitudinal Survey of Wealth, Income, Labor and Land (ELCA) and 4) the Cebu Longitudinal Health and Nutrition Survey from the Philippines. This section explains why I have chosen the CLHNS for my dissertation. Appendix A5 explains the caveats I found in the other three studies.

the outcomes of interests analyzed by [Glewwe, Jacoby, and King \(2001\)](#).

Data are also available on a non-verbal IQ test that was given to children in the first and second follow-up. The IQ test is called the Philippine Non-Verbal Intelligence Tests ([Guthrie, Tayag, and Jacobs, 1977](#)) and was properly adapted to the Filipino context. Non-verbal IQ in 1991 was the outcome variable studied by [Glewwe and King \(2001\)](#).

The CLHNS stands out from other longitudinal studies from developing countries because it includes questions that capture occupational aspirations. In the third follow-up (1998), adolescents were asked about their occupational aspirations with the following question: “*What kind of job would you like to do when you grow up?*”.⁵ The answer to this question has been codified using 117 Occupational Codes at a 3-digit level. The occupation performed by the mother and any other member of the household is available in the first, second and third follow-ups. They have also been coded with a high level of detail. Occupations reported in the first follow-up are classified into 67 2-digit occupational codes. Data on occupations are even richer in the second and third follow-ups because a 3-digit system was used.

Labor market performance of the participants in the study has been tracked since 2002. However, detailed occupational choices are not available in the two most recent follow-ups (2007 and 2009). This constraint implies that I should use occupational choices and labor market outcomes during 2005, the fifth follow-up. The subjects in the study were between 21 and 22 years old at that time and their occupational choices were summarized into 165 3-digit occupational codes. In conclusion, the CLHNS has rich data on occupational choices, occupational aspirations and individual skill proficiency.

The analysis is based on information for the current or most recent job held by respondents at the time of the 2005 follow-up survey. Self-employed individuals and employees of non-profit organizations are excluded, as well as unpaid family workers and those who

⁵Question B21, in the Employment Block (B) of the 1998 Follow-up questionnaire.

	1983	1991	1994	1998	2002	2005	2007	2009
	Base line	1st	2nd	3rd	4th	5th	6th	7th
Index Child data	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mother data	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-
Household data	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Community data	Yes	Yes	Yes	Yes	Yes	Yes	-	-
School data	-	-	Yes	-	-	-	-	-
Proficiency Scores								
General Cog. Skills		Non-verbal IQ test (100-items)	Same non-verbal IQ test					
Math			60-items test					
Reading, Cebuano			30-items test					
Reading, English			60-items test					
Number of Occ. Codes		52 codes	242 codes	140 codes		150 codes	-	-
1) Occ. aspiration	-	-	-	Yes	-	-	-	-
2) Parents' occupation	-	Yes	Yes	Yes	-	-	-	-

Table 3.1: Summary of the CLHNS (Philippines)

received work payments in kind. Workers who were not paid on a regular basis are also not included in the subsample. Hourly wage in pesos is equal to daily labor income divided by the usual number of hours worked per day. 38 observations with extreme values in hourly wage, daily labor income or hours worked per day are excluded. The final sample includes information for 554 women and 588 men.

Figure 3.1 reports the most frequent answers by gender when respondents were asked about their occupational aspirations in 1998. The pattern is different for men and women: around 27% of female respondents aspired to a teaching position, either in elementary or secondary school. The equivalent fraction among men was only 1.9%. To become a professional nurse was also a popular choice among women (8.8%), but not among men (0.3%). The most popular occupation among men was electrical or mechanical engineering (8.0%), but no women declared this particular engineering as their occupation of choice. Many of the preferred occupations among men are related to the shipping industry (engineer or deck officers) or the construction industry (architect, civil engineer, electrical fitter, carpenter). The medical profession (physicians) was much more popular among women

(2.9%) than men (0.7%). Interestingly, very few women and men were interested in the practice of law: only 0.9 % of women and 0.2 % of men had the occupational aspiration of becoming lawyers.

There were approximately seven years between the report of occupational aspirations (1998) and occupational choices (2005). It might have been a relative short time for individuals to achieve their occupational goal, especially if it required prolonged periods of post-secondary education. For example, no respondent was working as a physician, a lawyer or an architect by 2005. The most frequent occupational choices of men and women in 2005 can be found in Figure 3.2. There is a subset of occupations which were common choices for both men and women: waiters and waitresses, shellcraft workers, packers, salesmen and machine-tool operators. The gender occupational segregation reported by [Lee and Adair \(2011\)](#) is driven by other occupations. Consider the case of bricklayers: it was the most common occupation among men (9.5%), but no woman held such type of job in 2005. The opposite pattern of gender segregation happens with sewers and embroiderers: 5.2% of women held this occupation but only 0.5% of men did.

The results presented in Figures 3.1 and 3.2 suggest the match between occupational aspirations and occupational choices vary by gender. A formal test of this hypothesis are the first stage regressions which will be discussed in Section 3.6. The skill content of occupational aspirations will be used as instruments of the skill content of occupational choices. The instrumental variables will be relevant only if there is certain correlation between occupational aspirations and choices.

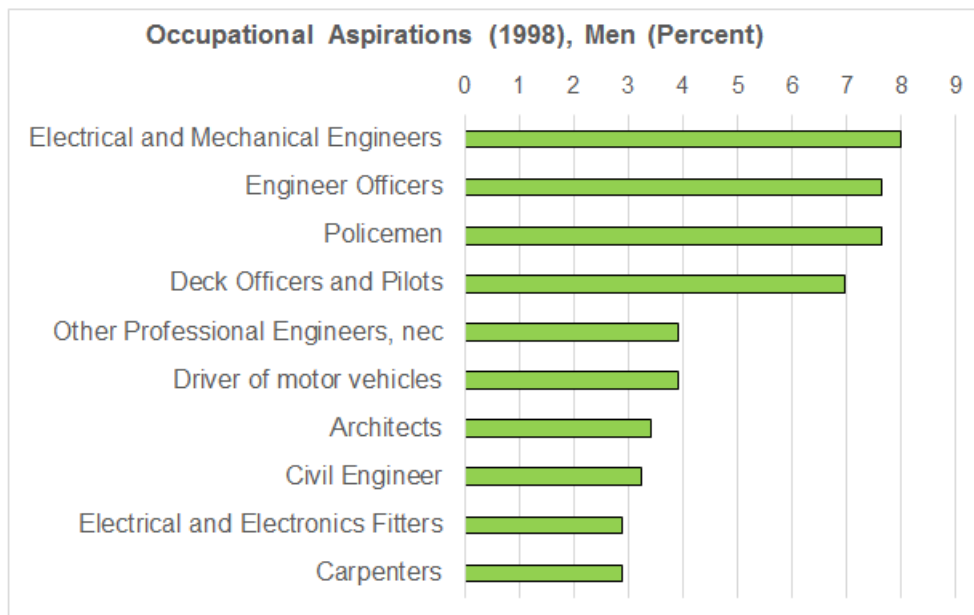
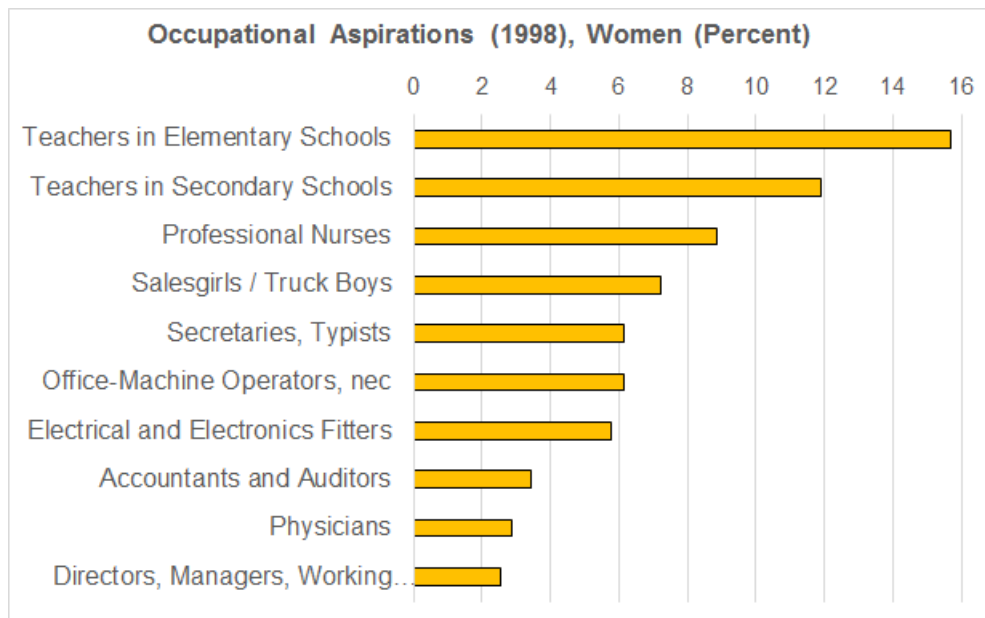


Figure 3.1: Top ten categories in occupational aspirations (1998)

Note: Women sample size = 554. Men sample size = 588. Calculations based on the CLHNS.

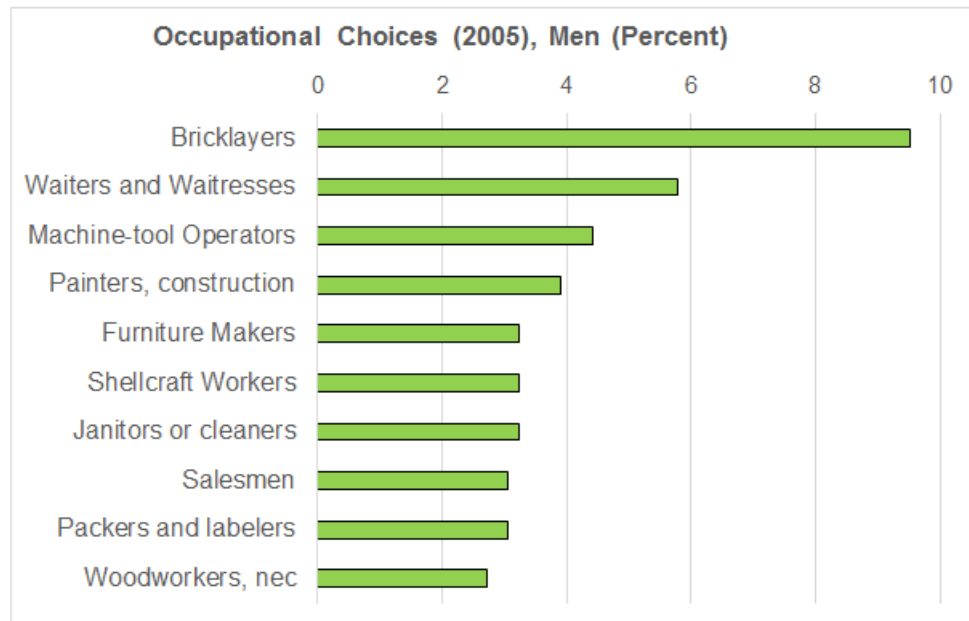
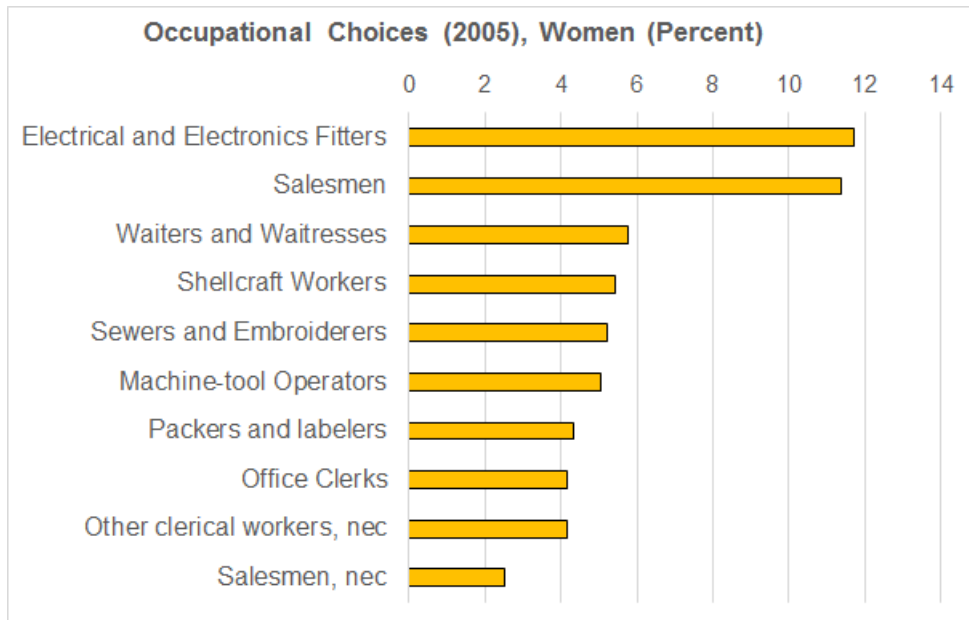


Figure 3.2: Top ten categories in occupational choices (2005)

Note: Women sample size = 554. Men sample size = 588. Calculations based on the CLHNS.

3.4 Survey of Filipino psychologists

The Occupational Information Network (O*Net) uses three sources of information: job incumbents, occupational experts and analysts. Job incumbents provide information on their own occupation. They report the main characteristics of their occupation based on their experience doing the job. Occupational experts are members of professional organizations who might have tangential experience, but are very knowledgeable about a particular industry and its related occupations. Analysts are industrial and organizational psychologists, with experience in human resource management. They provide information about large clusters of occupations and their opinions are based on their training and experience in work analysis, a branch of I/O psychology (Morgeson and Dierdorff, 2011).

One purpose of this paper was to collect data similar to O*Net for the Filipino economy on a limited budget, following the O*Net protocols used in the United States as close as possible (Tsacoumis and Willison, 2010). I received a \$1,000 grant from the Center for International Food and Agriculture Policy (CIFAP) to cover research costs. In order to stay within budget, the survey covered only I/O psychologists from the Philippines and focused on a narrow set of questions. Job incumbents or occupational experts were not interviewed. The O*Net skill data for the United States is based on the ratings of eight analysts; the data for the Philippines is based on ten respondents.

The CLHNS was a partnership between researchers at University of North Carolina at Chapel Hill (UNC) and the Office of Population Studies at the University of San Carlos, a private higher education institution located in Cebu City. The University of San Carlos has a Psychology department. They offer a B.A. in Psychology and a M.A. in Industrial and Organizational Psychology. Most alumni from their M.A program work for the business-process outsourcing industry (BPO) or in human resource departments across the Philippines.

I contacted several students and alumni from the University of San Carlos via *LinkedIn*.

I offered them economic compensation for filling out a survey based on the O*Net data collection instruments. I contacted a total of 15 psychologists and 10 of them agreed to answer the survey. All individuals I contacted complied with the following minimum criteria: 1) they were Filipino citizens living in the Central Visayas (Region VII of the Philippines); 2) they either had a B.A. in Psychology or an M.A. in I/O Psychology from the University of San Carlos; 3) they had at least two years of work experience in human resources; 4) they had at least basic English skills, according to their *LinkedIn* profile. There were seven women respondents and three men. Four respondents had a bachelor's degree, five had a master's degree and one had a PhD degree. Their median work experience was approximately five years. Each participant received between US\$ 90 and US\$ 120 as compensation for their professional services.

The public documentation for the CLHNS has the complete set of codes and titles used to categorize occupations in the raw data. The list contains 292 occupations, classified into the following 10 broad occupational categories:

- 0. Professional, Technical and Related Workers.
- 1. Administrative, Executive and Managerial Workers.
- 2. Clerical Workers.
- 3. Sales Workers.
- 4. Farmers, Fishermen, Hunters, Loggers and Related Workers.
- 5. Miners, Quarrymen and Related Workers.
- 6. Workers in Transport and Communication Occupations.
- 7. Craftsmen and Laborers.
- 8. Production-Process Workers.

- 9. Service, Sports and Related Workers.

Each respondent answered five questions about each one of the 292 occupations. The questions are based on O*Net questionnaires. First, they indicated the minimum level of education required to perform the job. They could choose one out of eight educational attainment levels, from no schooling to a post-graduate degree. The complete list of options can be found in Appendix A6. The remaining four questions explore the importance of reading, writing, speaking and math skills in each occupation. Respondents had to rate the skill's importance on a scale from 1 (Not important) to 5 (Extremely important). The precise definition of each skill and the instructions given to respondents can also be found in Appendix A6.

Each psychologist provided a total of 1,460 answers (= 292 occupations * 5 questions). Thus, I was concerned with the effect of respondents' fatigue. Several measures were taken to minimize the fatigue effect and guarantee data quality: ample time was given to all respondents to fill out the questionnaires. On average, they finished the task in eight days. 70% of the monetary compensation was paid only after I received and reviewed the finished product. Each respondent worked on a pre-formatted Excel file with validation rules. In addition, the order of occupations in each file was different. Since there were 10 broad occupational categories and 10 industrial psychologists, each one received an Excel file which began with a different broad category. By doing so, any possible fatigue effect would not be concentrated on the occupations which belong to the last broad categories.

According to Tsacoumis and Willison (2010), the quality of data collected in the United States is tested with two statistics: a measure of interrater reliability and the standard error of the average response. Table 3.2 reports the intraclass correlation for each one of the five questions. Tsacoumis and Willison (2010, p. 14) indicate that a rule-of-thumb in the psychology literature is to trust ratings with intraclass correlations above 0.80. This is the case for all the questions asked to Filipino psychologists.

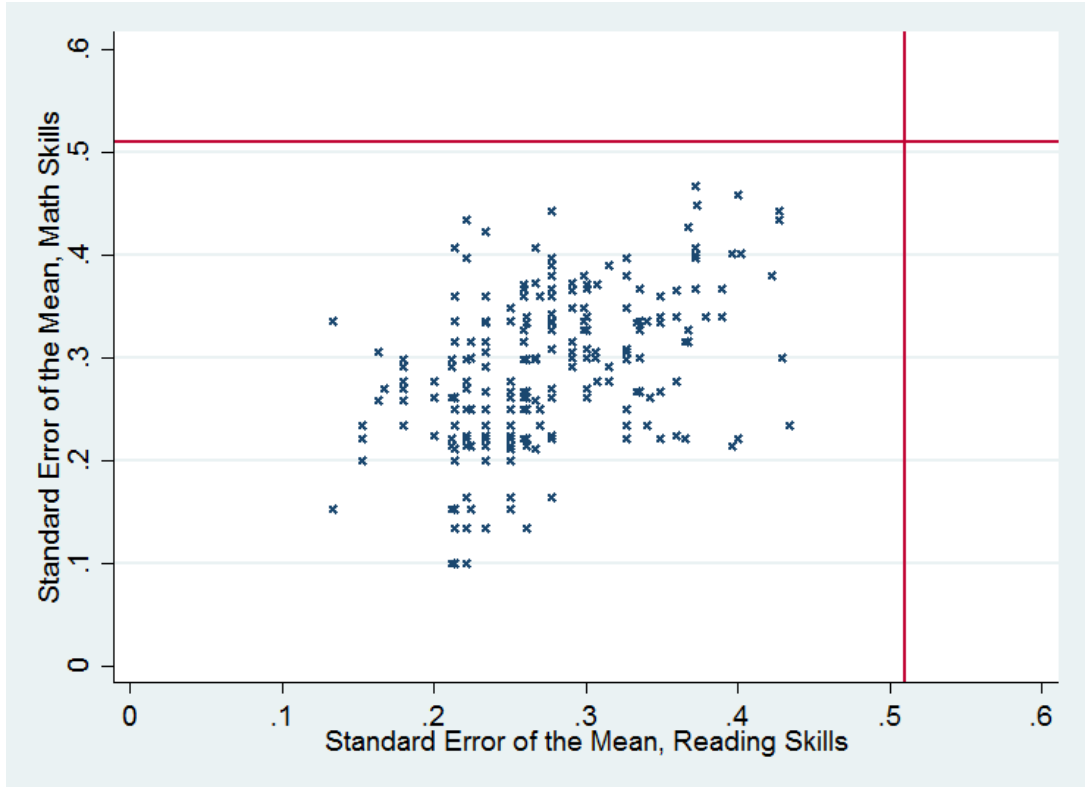


Figure 3.3: Standard error of the mean: math and reading skills

Note: each dot represents an occupation. There are 292 occupations in total. The number of raters is equal to 10.

	$ICC(3, k)$	95% Conf. Interval
Education Requirements	0.937	[0.926 , 0.948]
Reading Skills	0.955	[0.947 , 0.963]
Writing Skills	0.970	[0.965 , 0.975]
Speaking Skills	0.964	[0.957 , 0.970]
Math Skills	0.946	[0.937 , 0.955]

Table 3.2: Intraclass correlation coefficients

Note: the coefficients correspond to average consistency-of-agreement intraclass correlation coefficients (CA-ICC), denoted as $ICC(3, k)$ in [Shrout and Fleiss \(1979\)](#). Two-way mixed-effects models. Number of targets = 292 occupations. Number of raters = 10.

As for the standard error of the mean (SEM), [Tsacoumis and Willison \(2010, p. 13\)](#) argued the following: "if the SEM of the importance ratings for a given construct within an occupation was large (i.e. > 0.51), it was deemed to have insufficient agreement across raters." If the SEM is greater than 0.51, then the upper and lower bounds of a 95% confidence interval ($= 1.96 * SEM$) would be more than one unit away from the average rating. If this happened, then the O*Net research team asked the analysts to reconsider their ratings and argue the reason to support it. [Figure 3.3](#) plots the SEM for reading and math skills from the Filipino survey. No occupation surpasses the 0.51 cutoff and thus there was no need for the Filipino psychologists to reconsider their answers. In conclusion, the ratings collected for the Philippines pass same quality tests used in the United States.

The average rating of math and reading skills for the 292 occupations made by Filipino psychologists can be found in [Figure 3.4](#). Psychologists rated the importance of every skill for each occupation on a 1 to 5 scale. Therefore, the average rating is a continuous score within the same interval. I used the average ratings to score occupational aspirations and occupational choices in the CLHNS sample. By doing so, it is possible to test for the correlation in the skill content of occupational choices and aspirations.

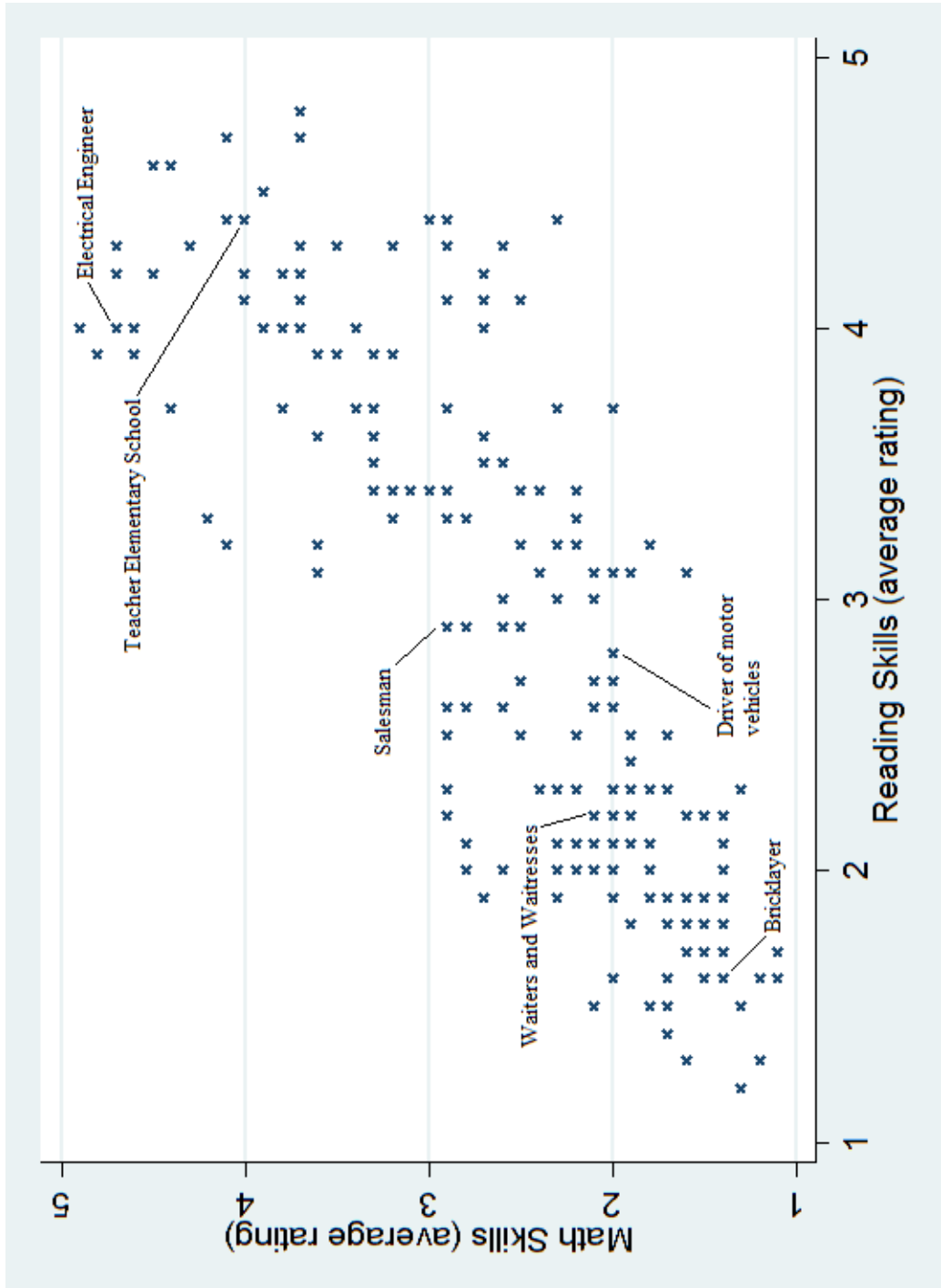


Figure 3.4: Average rating by Filipino psychologists, math and reading skills (292 occupations)

3.5 Econometric Framework

Consider the following wage equation, in which occupational choices are taken into account.

The occupation chosen by worker i is $k(i)$:

$$\ln(w_i) = \theta^w X_i + \beta^s p_i^s + \alpha^s r_{k(i)}^s + e_i \quad s \in \{R, M\} \quad (3.1)$$

The model focuses on one dimension of the skill content of occupations: either reading or math skills, $\{R, M\}$. A worker's wage depends on a vector of exogenous individual characteristics (X_i) and individual skill proficiency (p_i^s). Each occupation has an associated skill profile vector (r_k^R, r_k^M) , which measures the importance of reading and math skills for job performance. The component of the skill profile vector included in the wage equation (r_k^s) is endogenous because workers self-select into their occupations.

The goal of the regression analysis is to measure the wage return of occupational sorting. Therefore, α^s is the parameter of interest and a consistent estimate is obtained using instrumental variables. The associated first stage regression is the following:

$$r_{k(i)}^s = \theta^s X_i + \delta^s p_i^s + \gamma^s r_{z(i)}^s + u_i^s \quad s \in \{R, M\} \quad (3.2)$$

The occupational aspiration of worker i at age 15 is occupation $z(i)$. As a simplification, let z stand for $z(i)$ and k stand for $k(i)$. Consider the case of math: the importance of math skills for the occupation to which a worker aspired to in 1998 (r_z^M) is the instrumental variable for the importance of math skills for the occupation chosen by the same worker in 2005 (r_k^M). A similar explanation holds for the instrumental variable of reading skills.

The key identification assumptions are: 1) correlation in the skill content of occupational aspirations and occupational choices ($\gamma^R \neq 0$ and $\gamma^M \neq 0$), and 2) no correlation between the skill content of occupational aspirations and the error term in the wage equation ($Cov(r_z^R, e_i) = Cov(r_z^M, e_i) = 0$).

The skill content of occupations in the Philippines is measured using the average rating of the Filipino psychologists surveyed for this paper (see Section 3.4 and Figure 3.4). The importance of math and reading skills for occupational choices in 2005, based on the survey of Filipino psychologists, is denoted in the results section as $r_k^{R,PHP}$ and $r_k^{M,PHP}$. The equivalent vector for occupational aspirations in 1998 will be referred to as $r_z^{R,PHP}$ and $r_z^{M,PHP}$ in the results section.

3.6 Results

Women and men were analyzed separately, to determine if there were any differences in the patterns of occupational aspirations and choices. Tables 3.3 and 3.4 present basic summary statistics by gender. Table 3.5 contains mean differences and the statistical significance of the gap between women and men. Men in the sample earned on average 16% more of daily labor income than women in 2005, although women did better than men in reading, math and IQ tests back in 1994. The average skill content of occupations chosen by women in 2005 ($r_k^{R,PHP}, r_k^{M,PHP}$) was higher than the skill content of occupations chosen by men. In addition, women had higher occupational aspirations than men: the reading skill score for occupational aspirations declared back in 1998 ($r_z^{R,PHP}$) was higher for women than men.

The ratings used to score the skill content of occupations matter. To prove this point, consider the first stage regression defined by Equation 3.2. Occupational aspirations and choices could be scored using two alternative data sources: the O*Net database from the United States (USA) and the average rating of Filipino psychologists (PHP). Tables 3.6 and

3.7 present estimates by gender of Equation 3.2 based on ratings from the United States. The first column focuses on reading skills and the second column focuses on math skills. For the third column, the first principal component of math and reading skills was calculated and used to score each occupation.

There is no correlation between the skill content of aspirations and choices if O*Net is used to score occupations in the Philippines. The point estimates for γ^R and γ^M are statistically insignificant for both men and women (Tables 3.6 and 3.7). The low F statistics reveal a critical weak instruments problem if the analyses for the Philippines were to be based on ratings from the United States (all F statistics are below 3).⁶

Collecting data directly from Filipino psychologists made a difference. Tables 3.8 and 3.9 present estimates of the first stage regressions by gender if average ratings by Filipino psychologists are used to score occupational choices and aspirations. Tables 3.8 and 3.9 have the same column structure as Tables 3.6 and 3.7: the first column estimates Equation 3.2 for reading skills, the second column does the same for math skills and the third column is based on the first principal component of both skills. Note how individual skill proficiency plays a role in occupational sorting. Individual performance by women in reading and math tests back in 1994 is correlated with the corresponding skill content of occupations chosen in 2005. In the case of men, such correlation holds only for the reading test (variable p_i^R , coefficient δ^R).

There is a drastic difference in the predicted power of occupational aspirations for men and women, but only when the ratings by Filipino psychologists are used. Focus on Table 3.8: there is little correlation between the skill content of occupational aspirations and the skill content of occupational choices among women. The point estimate of γ^R is positive but statistically significant only at a 10% level (first column). The point estimate of γ^M

⁶I created an O*Net database of skill ratings coded with a 4-digit Census 2000 classification system, following the procedures used in the first chapter of this dissertation. With the research assistance of Jennifer Andrea Valbuena Fajardo, we mapped all the 292 occupations in the CLHNS codebooks to one 4-digit Census code. This process allowed me to score Filipino occupations using O*Net data.

is statistically not significant (second column). In addition, all F statistics are equal to or below 3. These first stages are not strong enough to carry out a valid instrumental variable estimation for women.

Continue now to the case of men, summarized in Table 3.9. There is evidence of a strong correlation in the skill content of aspirations and choices for men, as long as the adequate occupational rating system is used. The point estimate of γ^R is equal to 0.106 (s.e. = 0.026) and the point estimate of γ^M is 0.056 (s.e = 0.023). Both F statistics are above 5, but the model is much stronger for reading skills ($F = 16.4$) than math skills ($F = 6.0$). The correlation between the skill content of occupational aspirations of men in 1998 and their occupational choices in 2005 is strong enough to avoid a weak instruments problem and carry on with the instrumental variables estimation.

Recall Equation 3.1, the specification of the wage equation which captures the return to occupational sorting through parameter α^s . The analysis of the first stage regressions indicated that inference using instrumental variables is valid only for the subsample of men. These results are shown in Table 3.11. The first column presents the OLS estimates of the wage equation based on reading skills. The second column presents the equivalent instrumental variables estimates. The third and fourth columns depict OLS and IV results with a focus on math skills. The fifth and sixth columns used the first principal component of reading and math skills to score occupations and generate OLS and IV results.⁷

There is no evidence of a return to occupational sorting for men, after accounting for the endogeneity of occupational choice. OLS overestimated the return to occupational sorting (α^R and α^M) and underestimated the return to individual skill proficiency (β^R and β^M), when compared to the IV results. Proficiency in reading and math among men is correlated with daily labor income many years later, even after accounting for occupational choice.

⁷The instrumental variable estimates for women are not valid due to a weak instruments problem. However, the corresponding OLS and IV estimates can be found in Table 3.10, which has the same structure as Table 3.11.

3.7 Conclusions and Discussion

Occupational choice is a fundamental component of labor supply. This dissertation proposes an identification strategy to account for the endogeneity of occupational choice in wage equations: to instrument the skill content of occupational choices with the skill content of occupational aspirations. The implementation of the identification strategy requires two conditions: 1) longitudinal data in which occupational aspirations are declared many years before occupational choices are made, and 2) rating data to score occupations on the importance of different skills.

The CLHNS offers unique data from the Philippines to implement the identification strategy. Participants declared their occupational aspirations during adolescence (1998) and labor supply decisions were recorded in their early twenties (2005). Occupational characteristics have been measured for developed countries using surveys of job incumbents or job analysts, but there is a data void of occupational characteristics for developing countries. To the best of my knowledge, my dissertation is the first attempt to collect information on the skill content of occupations for a developing country, using the same instruments used in the United States for the Occupational Information Network.

This chapter shows it is possible to collect ratings from industrial psychologists around the world using a cost-effective procedure. I surveyed ten industrial psychologists from the Philippines. They provided answers on the importance of reading, writing, speaking and math skills for 292 occupations. The data collected complies with minimum quality controls. Their average rating was used to score occupational aspirations and occupational choices within the CLNHS data. Further research of occupational choice in other developing countries could use a similar approach to collect data on the skill content of occupations.

With continuous measures of the skill content of occupations, it is possible to set up an instrumental variables framework. The first stage regressions model occupational choice and the skill content of occupational aspirations works as the instrumental variable. The

second stage regressions correspond to wage equations, in which the parameter of interest is the wage return on occupational sorting.

There is a different pattern of occupational choices and aspirations by gender. On average, women worked in occupations with a higher skill content when compared to men. This result is consistent with the previous findings by [Lee and Adair \(2011\)](#). The first stage regressions based on the average ratings by Filipino psychologists revealed a mismatch between the occupational aspirations and occupational choices of women. On the contrary, there is evidence of a positive correlation between the skill requirements of men's occupational aspirations and occupational choices. Therefore, the identification strategy proposed by this dissertation is only valid for men within the CLHNS sample. I found no evidence of a return to occupational sorting among young men.

There could be two reasons behind the mismatch between aspirations and choices among women: 1) discriminatory conditions in the labor market might prevent women from obtaining employment in their preferred occupations, or 2) the occupational aspirations of women have a higher skill content, when compared to the aspirations of men. Such occupations might require more labor market experience or higher educational attainment. Since occupational choices were observed at a young age, it was more likely to find a positive correlation between the skill content of aspirations and the skill content of choices for men. Further research is required to distinguish between both hypotheses.

Table 3.3: Summary Statistics, Women Subsample

Variable		Mean	Std. Dev.	Min.	Max.	N
Labor income per day, Ln of Pesos, 2005		4.92	0.69	2.48	6.55	554
Non-verbal IQ, 1994		0.08	0.95	-2.81	2.32	554
Reading test, 1994	p_i^R	0.27	0.99	-1.72	2.58	554
Math test, 1994	p_i^M	0.19	0.96	-2.07	2.52	554
Current Occupation, 2005: Reading skills	$r_k^{R,PHP}$	2.53	0.71	1.3	4.4	554
Current Occupation, 2005: Math skills	$r_k^{M,PHP}$	2.31	0.73	1.1	4.7	554
Occupational Aspirations, 1998: Reading skills	$r_z^{R,PHP}$	3.64	0.88	1.7	4.7	554
Occupational Aspirations, 1998: Math skills	$r_z^{M,PHP}$	3.37	0.85	1.3	4.9	554

Table 3.4: Summary Statistics, Men Subsample

Variable		Mean	Std. Dev.	Min.	Max.	N
Labor income per day, Ln of Pesos, 2005		5.07	0.45	3.04	6.8	588
Non-verbal IQ, 1994		-0.04	0.96	-3.84	2.57	588
Reading test, 1994	p_i^R	-0.26	0.91	-1.89	2.58	588
Math test, 1994	p_i^M	-0.15	0.93	-2.06	2.43	588
Current Occupation, 2005: Reading skills	$r_k^{R,PHP}$	2.18	0.59	1.3	4.4	588
Current Occupation, 2005: Math skills	$r_k^{M,PHP}$	1.97	0.6	1.1	4.7	588
Occupational Aspirations, 1998: Reading skills	$r_z^{R,PHP}$	3.27	0.95	1.5	4.7	588
Occupational Aspirations, 1998: Math skills	$r_z^{M,PHP}$	3.25	1.21	1.1	4.9	588

Table 3.5: Differences between women and men

Variable	Difference	Std. Error	t Stat.
Labor income per day, Ln of Pesos, 2005	-0.15	0.034	-4.41
Non-verbal IQ, 1994	0.12	0.057	2.11
Reading test, 1994 (p_i^R)	0.52	0.057	9.12
Math test, 1994 (p_i^M)	0.34	0.056	6.07
Current Occupation, 2005: Reading skills ($r_k^{R,PHP}$)	0.35	0.039	8.97
Current Occupation, 2005: Math skills ($r_k^{M,PHP}$)	0.34	0.039	8.72
Occupational Aspirations, 1998: Reading skills ($r_z^{R,PHP}$)	0.37	0.054	6.85
Occupational Aspirations, 1998: Math skills ($r_z^{M,PHP}$)	0.11	0.061	1.80

Table 3.6: First Stage Results: ONet Ratings, Women subsample

Current Occupation	Reading ($r_k^{R,USA}$)	Math ($r_k^{M,USA}$)	R-M ($r_k^{RM,USA}$)
Reading test, 1994 (p_i^R)	0.083*** (0.023)		0.157*** (0.059)
Math test, 1994 (p_i^M)		0.062* (0.034)	0.065 (0.060)
Occ. Aspiration: Reading ($r_z^{R,USA}$)	0.079 (0.049)		
Occ. Aspiration: Math ($r_z^{M,USA}$)		0.052 (0.048)	
Occ. Aspiration: R-M ($r_z^{RM,USA}$)			0.058 (0.043)
R^2	0.19	0.15	0.22
F statistic	2.596	1.189	1.862
Observations	554	554	554

Standard errors in parentheses

Heteroskedasticity-robust s.e. Additional controls: age, marital status, village of birth, and IQ in 1994.

Current Occupation: workers' occupation in 2005 was scored using ONet math and reading skills scores.

Occupational Aspirations: workers' occupational aspirations in 1998 were scored using ONet.

R-M: occupations scored with the first principal component of ONet math and reading skills.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7: First Stage Results: ONet Ratings, Men subsample

Current Occupation	Reading ($r_k^{R,USA}$)	Math ($r_k^{M,USA}$)	R-M ($r_k^{RM,USA}$)
Reading test, 1994 (p_i^R)	0.058*** (0.021)		0.050 (0.050)
Math test, 1994 (p_i^M)		0.048 (0.030)	0.086 (0.056)
Occ. Aspiration: Reading ($r_z^{R,USA}$)	0.024 (0.037)		
Occ. Aspiration: Math ($r_z^{M,USA}$)		0.044 (0.032)	
Occ. Aspiration: R-M ($r_z^{RM,USA}$)			0.024 (0.033)
R^2	0.14	0.11	0.14
F statistic	0.425	1.993	0.552
Observations	588	588	588

Standard errors in parentheses

Heteroskedasticity-robust s.e. Additional controls: age, marital status, village of birth, and IQ in 1994.

Current Occupation: workers' occupation in 2005 was scored using ONet math and reading skills scores.

Occupational Aspirations: workers' occupational aspirations in 1998 were scored using ONet.

R-M: occupations scored with the first principal component of ONet math and reading skills.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.8: First Stage Results: Filipino Ratings, Women subsample

Current Occupation	Reading ($r_k^{R,PHP}$)	Math ($r_k^{M,PHP}$)	R-M ($r_k^{RM,PHP}$)
Reading test, 1994 (p_i^R)	0.152*** (0.037)		0.102** (0.048)
Math test, 1994 (p_i^M)		0.118*** (0.042)	0.072 (0.052)
Occ. Aspiration: Reading ($r_z^{R,PHP}$)	0.055* (0.031)		
Occ. Aspiration: Math ($r_z^{M,PHP}$)		0.048 (0.037)	
Occ. Aspiration: R-M ($r_z^{RM,PHP}$)			0.041 (0.034)
R^2	0.23	0.18	0.22
F statistic	3.049	1.725	1.477
Observations	554	554	554

Standard errors in parentheses

Heteroskedasticity-robust s.e. Additional controls: age, marital status, village of birth, and IQ in 1994.

Current Occupation: scored with avg. rating of 10 Filipino HR Specialists.

Occupational Aspirations: occ. aspirations in 1998 scored with avg. rating of 10 Filipino HR Specialists.

R-M: occupations scored with the first principal component of math and reading Filipino ratings.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.9: First Stage Results: Filipino Ratings, Men subsample

Current Occupation	Reading ($r_k^{R,PHP}$)	Math ($r_k^{M,PHP}$)	R-M ($r_k^{RM,PHP}$)
Reading test, 1994 (p_i^R)	0.140*** (0.033)		0.119*** (0.040)
Math test, 1994 (p_i^M)		0.059 (0.039)	0.011 (0.045)
Occ. Aspiration: Reading ($r_z^{R,PHP}$)	0.106*** (0.026)		
Occ. Aspiration: Math ($r_z^{M,PHP}$)		0.056** (0.023)	
Occ. Aspiration: R-M ($r_z^{RM,PHP}$)			0.074*** (0.024)
R^2	0.17	0.10	0.15
F statistic	16.417	6.094	9.510
Observations	588	588	588

Standard errors in parentheses

Heteroskedasticity-robust s.e. Additional controls: age, marital status, village of birth, and IQ in 1994.

Current Occupation: scored with avg. rating of 10 Filipino HR Specialists.

Occupational Aspirations: occ. aspirations in 1998 scored with avg. rating of 10 Filipino HR Specialists.

R-M: occupations scored with the first principal component of math and reading Filipino ratings.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.10: OLS and IV Wage Equation Results: Filipino Ratings, Women subsample

	(1)	(2)	(3)	(4)	(5)	(6)
Reading test (p_i^R)	0.092** (0.036)	0.253* (0.130)			0.051 (0.046)	0.260 (0.199)
Math test (p_i^M)			0.120*** (0.041)	0.348* (0.193)	0.082 (0.051)	0.241 (0.169)
Current Occupation: Reading ($r_k^{R,PHP}$)	0.118** (0.046)	-0.882 (0.793)				
Current Occupation: Math ($r_k^{M,PHP}$)			0.059 (0.043)	-1.704 (1.411)		
Current Occupation: R-M ($r_k^{RM,PHP}$)					0.090** (0.045)	-1.896 (1.708)
R^2	0.17	.	0.17	.	0.17	.
Model	OLS	IV	OLS	IV	OLS	IV
Observations	554	554	554	554	554	554

Standard errors in parentheses

Heteroskedasticity-robust s.e. Additional controls: age, marital status, village of birth, and IQ in 1994.

Current occupations were scored with the average rating of 10 Filipino HR Specialists.

Dependent variable: Labor income per day, Ln of Pesos, 2005

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.11: OLS and IV Wage Equation Results: Filipino Ratings, Men subsample

	(1)	(2)	(3)	(4)	(5)	(6)
Reading test (p_i^R)	0.067** (0.026)	0.072* (0.043)			0.053* (0.028)	0.072* (0.043)
Math test (p_i^M)			0.074** (0.030)	0.091** (0.037)	0.038 (0.032)	0.042 (0.031)
Current Occupation: Reading ($r_k^{R,PHP}$)	0.093*** (0.032)	0.058 (0.208)				
Current Occupation: Math ($r_k^{M,PHP}$)			0.053* (0.031)	-0.178 (0.318)		
Current Occupation: R-M ($r_k^{RM,PHP}$)					0.072** (0.031)	-0.082 (0.255)
R^2	0.15	0.15	0.14	0.05	0.15	0.11
Model	OLS	IV	OLS	IV	OLS	IV
Observations	588	588	588	588	588	588

Standard errors in parentheses

Heteroskedasticity-robust s.e. Additional controls: age, marital status, village of birth, and IQ in 1994.

Current occupations were scored with the average rating of 10 Filipino HR Specialists.

Dependent variable: Labor income per day, Ln of Pesos, 2005

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 4

Same Program, Different Outcomes: Understanding Differential Effects from Access to Free, High-Quality Early Care

with Aaron Sojourner^{1,2}

4.1 Introduction

Evidence from human and animal studies shows that the brain develops critically-important neural structures and functions during pregnancy and the first few years after birth, which in turn shape long-run cognitive, social, emotional development and health outcomes ([Sapolsky, 2004](#); [Knudsen et al., 2006](#)). Moreover, brain development differs between children

¹Assistant Professor, Carlson School of Management, University of Minnesota

²Juan Chaparro and Aaron Sojourner contributed equally to this work

born into low-, middle-, and high-socioeconomic status (SES) families. [Hanson et al. \(2013\)](#) study of early brain structure development and find that the relationship between SES and average gray-matter volume is weak in the first year of life. However, large SES-based gaps emerge between ages 1 and 3 as average gray-matter volume becomes strongly and positively correlated with SES.

These structural differences are matched by the variation in behavioral measures of cognitive skills (e.g., IQ and achievement tests) assessed in the early years of children's lives. By age 5, reading and math achievement is strongly correlated with family income ([Heckman, 2006](#); [Reardon, 2011](#); [Figlio and Guryan, 2014](#)). Gaps in cognitive and other skills that exist at that point tend to persist throughout childhood and to have strong relationships with adult productivity ([Cunha et al., 2006](#)).

Improving the quality of children's environments at very early ages can raise skill levels in both the short- and long-run ([Phillips, Shonkoff et al., 2000](#); [Ramey, Campbell, and Ramey, 1999](#); [Duncan and Magnuson, 2013](#)). Compelling, policy-relevant evidence comes from experiments where, among participating families, some are randomly selected for the offer of free access to high-quality, early childhood care environments for their children along with supplementary services (treatment group) and other families are not (control group). The positive average treatment effects on child cognitive skill from many studies provide compelling evidence that environment matters for child development.

While experimental designers and policy makers can offer particular programs to parents, the effects of these offers on children's development depend critically on how parents react to the offers. This paper examines the following questions theoretically and empirically:

1. To what extent do families take up an offer of high-quality care during child ages 12 to 36 months?

2. What kinds of environments are crowded out of the child's experience by the take-up?
How do parents use any time freed by taking up the offer of free care?
3. How does this combination of take-up and other choices affect child development?
4. Furthermore, how do these choices differ across various kinds of families? What dimensions of children and families drive any differential responses?

The same treatment offer can have quite different effects on different kinds of children and families. Impacts on cognitive skill appear larger for children from lower-income families (Gormley, Phillips, and Gayer, 2008; Duncan and Sojourner, 2013; Cascio and Schanzenbach, 2013). Impacts also appear larger for children born heavier rather than very low birth weight (Gross, Spiker, and Haynes, 1997). Heterogeneity on birth weight and family income are interesting and suggestive but neither dimension is ideal for understanding the fundamental economic choices that drive heterogeneity. For instance, birth weight reflects at least three distinct influences: characteristics of the family and mother fixed prior to pregnancy, choices that the mother made during her pregnancy that influence the child's condition at birth, and a random component that would generate differences in birth condition even among those with the same characteristics and prenatal choices. Family income also reflects at least three, distinct influences: an hourly wage available to any parent is largely set by a market outside their control, parents' choices about how many hours to work in the labor market, as well as sources of non-labor income. Two parents with the same potential wage and the same in other environmental circumstances may choose to work different numbers of hours and end up with different family incomes due to differences in the value they place on work, leisure, or parenting. Income reflects a choice. Potential wage is relatively fixed at a given point in time and summarizes the parent's expected labor-market productivity, which may be correlated with the parent's productivity in producing child skill through parenting as well.

Understanding what drives heterogeneous effects is essential to designing child-care or

family subsidy policies. Policy implications depend on the extent to which differences in child-skill effects of offers of subsidized care are driven by differences in (a) the opportunity cost of parents' time (potential wage), (b) parents' willingness to expend available time, money, and effort to build children's skills rather than using those resources for other purposes holding other aspects of the situation fixed (tastes), or (c) biological differences fixed at birth (endowment) that may create differences in the productivity of postnatal influences. This paper makes both theoretical and empirical contributions to understanding the drivers of heterogeneity in effects.

First, we propose a model of early childhood cognitive skill formation and maternal pre- and post-natal investment choice that combines features of some existing models (Ribar, 1995; Kimmel and Connelly, 2007; Cunha, Heckman, and Schennach, 2010; Bernal and Keane, 2011), while adding key innovations including endogenous parenting effort and a framework for analyzing maternal and non-maternal care through a unified lens. The model is of a mother with one child.³ The child requires some type of care – either maternal or non-maternal – at all times. The mother has a money budget, with expenditures split between non-maternal child care and consumption, and a time budget split among labor-market work, parenting, and all other uses, which is broadly defined as leisure. Time spent providing maternal care requires foregoing wages and leisure. Each care type has an endogenous quality level, which is defined by how well it promotes the development of child cognitive skills. Higher quality and larger quantities of non-maternal care can be purchased with money. For a given mother, increasing maternal-care quantity or quality requires additional parenting effort. On the margin, additional parenting effort is a source of disutility for the mother. Integrating both parenting margins is a novel contribution of our paper and captures essential economic tradeoffs parents face. The model allows for heterogeneity in maternal tastes, maternal labor-market productivity, and maternal productivity in parenting, including possible correlations between labor market productivity

³The theory could equivalently be framed as one parent and one child. However, in the data we analyze, there is careful attention paid to mothers. A maternal frame is used only for a smoother connection between theory and data. We regret any sexist overtones this generates.

and parenting productivity. We derive first-order conditions and corner solutions that characterize the optimal choices for trading off maternal leisure, consumption, parenting effort, and child-skill development. Maternal responses with respect to maternal time use, maternal parenting effort and maternal-care quality, quantities and qualities of nonmaternal care, and other margins are studied. The model illuminates important economic tradeoffs parents face and potential drivers of these choices.

To develop empirical evidence, we study data from the Infant Health and Development Program (IHDP), which offered a package of services including free, full-day, Abecedarian-type early education to a randomly chosen subset of 985 children in eight sites scattered around the United States (Bradley et al., 1994; Gross, Spiker, and Haynes, 1997). Eligible babies were born low birth-weight ($\leq 2,500$ g) and premature (≤ 37 weeks gestation). Eligibility was not restricted by family income, race or ethnicity. A demographically-heterogeneous set of children and families enrolled in the study.

The IHDP treatment provided weekly home visits from a paraprofessional during the first year of life and up to nine hours of daily child care at an IHDP-run child development center (CDC) in each city when the child was age 12 to 36 months. The CDCs used a game-based curriculum that emphasized language development. A high-quality evaluation design included random assignment into treatment and assessment of intelligence quotient (IQ) and other outcomes. A series of papers reported treatment effects on various outcomes in various subsamples such as child cognitive skill and behavior (Brooks-Gunn et al., 1993), quality of the home environment (Bradley et al., 1994), quality of parenting, maternal employment (Brooks-Gunn et al., 1994), and the use of paid child care (Gross, Spiker, and Haynes, 1997). Berlin et al. (1998) studied mechanisms focusing especially on heterogeneity along demographic lines. They find that child cognitive effects are larger among those who take-up more care. Though the reduced-form treatment effect of the IHDP intervention on child cognitive skill is known to vary by birth weight and maternal education and by income (Duncan and Sojourner, 2013), there is more to learn about the channels creating

this heterogeneity.

This paper contributes to the literature by studying heterogeneity in the IHDP along dimensions informed by economic theory. The IHDP provides a rich context to learn about heterogeneity in parental responses to an offer of free, high-quality care and how this relates to heterogeneity in child skill. First, the offered care constituted a powerful, positive shock to children’s early environments on average. Second, it was randomly-assigned, generating credible causal identification. Third, the IHDP collected data on many margins of children’s experiences, family characteristics, and parental choices for both the treatment and control groups. In some cases, the IHDP data does not contain explicit measures of theoretically-important factors and we construct proxies for these latent factors by combining IHDP data with supplementary sources. This permits us to carefully characterize families in theoretically-relevant dimensions that may drive heterogeneity in parental choices and provides many response margins to use as outcomes. Differences in parent’s post-natal investment choices may be driven by a variety of differences including especially 1) differences in the value of their time in the labor market and in parenting (potential wage and productivity), 2) differences in their willingness and ability to expend available time, money, and effort to build child’s human capital rather than to use those resources for other purposes holding fixed the amounts of resources available (tastes), and 3) differences in their child’s condition at birth – weight or gestational age at birth – holding fixed observed family and prenatal influences.

Maternal potential wage is relatively straightforward to estimate using standard econometric methods. We do not directly observe mothers’ wage in the IHDP, even for those who work. To build a wage proxy, we estimate a standard female labor supply model using a sample of mothers of young children from the Current Population Survey (CPS) over the same years. This delivers coefficients that relate expected potential wage to maternal and family characteristics, such as age, education level, marital status, and number of children of different ages. Using these coefficients, we score mothers in the IHDP using the same set

of predictors to get a measure of each IHDP mother’s expected potential wage.

There is no standard way to disentangle differences in child condition at birth from differences in parental tastes. However, this is important in unpacking the drivers of heterogeneous treatment effects by birth weight. Parental tastes influence prenatal investment choices and, thereby, influence child condition at birth. Tastes continue to influence postnatal investment choices. Random shocks to conditions at birth can also have an independent effect on postnatal choices. For instance, consider a child born at particularly low weight or particularly premature compared to other children born in similar families by mothers who made similar prenatal investment choices; refer to this as a low level of child endowment or a bad shock to condition at birth. It is plausible that a parent would respond by adding extra, compensating investment, creating a negative correlation between child endowment and postnatal investments ([Almond and Mazumder, 2013](#)). Looking at heterogeneity in postnatal investment choices by birth weight, it has not been clear whether the differences are due to differences in parental productivity, differences in maternal tastes, or differences in child endowment.

Unlike postnatal investment choices, prenatal choices are made under a veil of ignorance with respect to child endowment ([Aizer and Cunha, 2012](#)). Therefore, mothers’ pre-natal investment choices – such as number of cigarettes smoked or amount of drugs and alcohol used during pregnancy – provide important information about maternal willingness to trade personal consumption utility against utility from future child human capital that is relatively uncontaminated by any post-natal reaction to information revealed at birth about the child’s endowment. We develop a new method of disentangling parental tastes from child endowment based on this idea, which then allows us to measure each of these in each IHDP family and to study heterogeneity in effects along these lines.

We draw on the nationally-representative Early Childhood Longitudinal Study, Birth Cohort (ECLS-B) and estimate how prenatal investment choices and maternal characteristics predict birth weight and gestational age. Then, we score each mother-child pair in the

ECLS-B on a pre-natal investment index and an index of child endowment, measured as the deviation of the child's realized birth status from its conditional expectation, yielding new nationally-representative estimates of the joint distribution of indexes of pre-natal investment and child endowment. Next, we score each mother-child pair in the IHDP with this model and, thereby, characterize them in the national distribution in terms of prenatal investment level and child endowment. We consider the prenatal investment index as a proxy for maternal preference for child human capital in our analysis of postnatal investment choices and the child endowment as potentially important in governing the productivity of postnatal investments. Taken together, this gives a useful, theoretically-informed characterization of maternal and child type.

This approach is useful primarily because it allows us, when looking at children born at the same weight to demographically-similar mothers, to parsimoniously separate maternal tastes and child endowment. Children may end up at the same birth weight via low prenatal investment and high endowment shock or high investment and low shock.

In the end, we find evidence that measured heterogeneity in the opportunity costs of mothers' time is the most important in driving heterogeneous treatment effects while proxies for differences in maternal valuation of child human capital and biological differences fixed at birth explain much less.

4.2 Conceptual Framework

A public policy intervention, which has a standardized design and has been implemented uniformly across households, might produce different consequences among the participants. Such effect heterogeneity occurs because households react to policy interventions according to their preferences, resource constraints, and other factors. Our conceptual framework focuses on the economic decisions faced by participants in the IHDP about how to allocate

their time, money, and effort between alternative uses, each of which has different consequences for parents and children. Households have different preferences about consumption, human development of their children, and time allocation between market and non-market activities. They also differ in the economic resources available to satisfy their needs. The conceptual framework brings together all these pieces in a one-period utility maximization problem, in which parents decide how to allocate their available resources to provide proper care to their child. We will refer to all care received by a child between birth and age 3 as postnatal investment.

4.2.1 An Economic Model of Post-natal Investment

Suppose early childhood cognitive skill is produced according to:

$$h = \tilde{f}(I_1, h_0, \varepsilon) \tag{4.1}$$

In particular, allow age-3 IQ to depend on post-natal investment (I_1), the stock of human capital at birth (h_0), and unmeasured, post-natal productive heterogeneity (ε). [Cunha and Heckman \(2007\)](#) focused labor economists on trying to understand the dynamic complementarity of investments. Dynamic (or inter-temporal) complementarity captures how the productivity of current investment depends on the incoming stock of skill, embodying past investment and the innate endowment. In the present context, this key property of the human capital production function is $\tilde{f}_{12} = \frac{\partial^2 \tilde{f}}{\partial I_1 \partial h_0}$. It is interesting because it has a strong influence on the optimal timing of investments.

We also explore the productive relationship between two kinds of post-natal investments: embodied in maternal and non-maternal care. For child skill development, quality of care matters. Every child requires supervision and care for a total of $T_c = 168$ waking hours per week, creating a child time budget. This is common across all children.

$$r + n + t = T_c \text{ [1: child time constraint]} \quad (4.2)$$

The distribution of developmentally-relevant care quality and type varies. Allowing for the possibility that maternal care is special, we consider two kinds of care: maternal and non-maternal such that maternal care hours (r) plus non-maternal care hours ($n + t$) must total T_c . This constitutes the child's time budget constraint. Non-maternal care encompasses many arrangements, such as care by other relatives or purchased child care services. The qualities of maternal care (q^r) and non-maternal care (q^n) also vary. Post-natal investment depends on quality-adjusted effective units of maternal and non-maternal care:

$$I_1 \equiv g(q^n n, q^r r) \quad (4.3)$$

In the context of the IHDP, a special source of non-maternal care is available to those in the treatment group (t). Households in the treatment group can use the child development center (CDC) services for up to $\bar{\tau} = 45$ hours per week. Mothers choose how many hours to take up.

$$t \leq \bar{\tau} \text{ [2: maximum CDC time]} \quad (4.4)$$

In the control group, no CDC hours are available, $\bar{\tau} = 0$. The quality of free CDC daycare is exogenous and equal to q^t . Effective units of CDC care are equal to $q^t t$. Effective units of non-maternal care become the sum of effective units of CDC care and other nonmaternal care: $q^t t + q^n n$. Effective units of care are a central concept in the model and Table 4.1 summarizes them. These are the investment inputs of the child's human capital production function. Combining \tilde{f} and g yields the production function:

$$h = f [q^n n + q^t t ; q^r r ; h_0, \varepsilon] \quad \textbf{[3: human capital production technology]} \quad (4.5)$$

Each mother also has a time constraint. She divides her time endowment (T_p) between three types of activities. Maternal child care (r), as previously discussed, is one. Leisure (l) and wage work (L) are the others.

$$r + L + l = T_p \quad \textbf{[4: mother's time constraint]} \quad (4.6)$$

The mother can earn a potential wage per hour (w), which is an increasing function of observed human capital (m) and unobserved ability (ω):

$$w = w(m, \omega) \quad \textbf{[5: wage offer]} \quad (4.7)$$

Total income equals labor earnings plus any exogenous non-labor income (Y). Total income can be used to purchase child care in the market or to pay for consumption (c). Regarding non-maternal, non-CDC sources of care, mothers choose both how much time to use (n) and the quality of care (q^n). These have a non-negative and exogenous price equal to π per each unit of effective care received.

$$c + \pi q^n n = wL + Y \quad \textbf{[6: Budget constraint]} \quad (4.8)$$

The quality of maternal care (q^r) depends on the mother's human capital (m), unobserved individual heterogeneity in ability (ω), and instantaneous parenting effort (e):

$$q^r = q^r(m, \omega, e) \text{ [7: maternal-care quality technology]} \quad (4.9)$$

This allows the wage offer (w) and the quality of maternal care (q^r) to be correlated due to observed maternal characteristics, like maternal education or unobserved maternal heterogeneity in ability. We assume (m, ω) are given but mothers choose the level of parenting effort they invest.

Maternal preferences are represented by $U(c, l, p, h, t)$. Utility increases in consumption (c), leisure hours (l), and the child's human capital (h), but decreases in total parenting effort (p) and time the child spends at the CDC (t). The mother chooses $(c, q^n, n, e, r, l, L, t)$. Total parenting effort is the product of the instantaneous effort level (e) and effort duration, that is hours of maternal care provided (r).

$$p = er \text{ [8: Total parenting effort]} \quad (4.10)$$

This parenting quality-quantity tradeoff has been missing from the economics literature, perhaps because datasets with both parenting time and parenting quality are rare. This captures the idea that high-quality parenting is more difficult to maintain over longer periods than shorter periods. Parenting can be exhausting.⁴

Some distaste for free CDC services is required to explain incomplete take-up of high-quality, free care, similar to [Bernal and Keane \(2010\)](#). This distaste captures individual heterogeneity in felt stigma or logistical challenges in using the CDC, such as perhaps

⁴The utility function assumes a negative marginal utility to parenting effort. What about the possibility that parents derive positive utility from parenting? The focus is here on the margin, not on the first hour of parenting. Conventional labor-leisure choice models assume that the marginal utility of labor is negative, despite the fact that we might enjoy the first hour of our jobs. This assumption on parenting is similar. If there were no cost to parenting effort, we would get unboundedly high parenting time and effort. Everyone chooses a positive level of leisure hours. Another way of understanding this is to say that maybe there is both an indirect utility payoff from parenting effort through increased child human capital (which we capture) and a direct payoff (which we shut down). Any direct payoff will be interpreted as an especially high taste for child human capital.

working nights or having multiple young children, with only one eligible for CDC care.

A full income - full consumption budget constraint is obtained by combining the child and mother's time constraints with the budget constraint. This simplifies the constraints and yields the following expression:

$$c + [\pi q^n - w] n + wl = w [T_p - T_c] + wt + Y \quad (4.11)$$

Full income, which corresponds to the right hand side of (4.11), is derived from non-labor income, total free daycare time valued at the parent's market wage and net parental time endowment, also valued at the market wage. On the other hand, full consumption has three components. The first one is traditional consumption. The second one is total value of other sources of care, like purchased daycare. Focus on the economic cost of this decision, which is $\pi q^n - w$: one additional hour of daycare with quality q^n will cost the parent a total of πq^n monetary units, but this decision will free up one hour of parental time, which has a labor market value of w . The third component of full consumption is leisure time priced at the market wage. We can now write the post-natal problem as:

$$\text{Max}_{c, q^n, e, n, l, t} U(c, l, p, h, t) \quad \text{s.t.} \quad (4.12)$$

$$c + [\pi q^n - w] n + wl = w [T_p - T_c] + wt + Y \quad (4.13)$$

$$h = f [q^n n + q^t t ; q^r r ; h_0, \varepsilon] \quad (4.14)$$

$$t \leq \bar{t} \quad (4.15)$$

$$p = er \quad (4.16)$$

4.2.2 Optimal Post-natal Investment and Economic Interpretation

This section describes properties of the optimal choices formally and discusses the economic tradeoffs behind these decisions. The solution to the post-natal parental problem is given by a vector of eight variables $(\lambda^*, \mu^*, c^*, q^{n^*}, e^*, n^*, l^*, t^*)$ which comply with all the Kuhn-Tucker conditions available in Appendix A7. Optimal labor supply (L^*) and optimal parental care (r^*) will be given by:

$$r^* = T_c - n^* - t^* \quad (4.17)$$

$$L^* = T_p - l^* - r^* \quad (4.18)$$

The following expressions are based on the Kuhn-Tucker conditions, but use the marginal rates of substitution (MRS) which are more suitable for economic interpretation. These first order conditions focus on solutions where the budget constraint is binding ($U_c = \lambda^* > 0$) and parents do not use all the hours available for them at the CDC ($0 \leq t^* < \bar{t} ; \mu^* = 0$), because this is a predominant characteristic in the IHDP data. We contemplate cases where the mother could decide not use help from other caretakers ($n^* \geq 0$). Finally, for a more transparent presentation of the first order conditions, we will focus only on interior solutions for c^* , q^{n^*} , e^* and l^* .

$$\frac{\partial \mathcal{L}}{\partial l} : MRS_{l,c} = w \quad (4.19)$$

$$\frac{\partial \mathcal{L}}{\partial t} : MRS_{h,c} [f_1 q^t - f_2 q^r] + w - MRS_{p,c} e \leq -MRS_{t,c}; \quad \frac{\partial \mathcal{L}}{\partial t} t = 0; \quad 0 \leq t < \bar{\tau} \quad (4.20)$$

$$\frac{\partial \mathcal{L}}{\partial n} : MRS_{h,c} [f_1 q^n - f_2 q^r] + w - MRS_{p,c} e \leq \pi q^n; \quad \frac{\partial \mathcal{L}}{\partial n} n = 0; \quad n \geq 0 \quad (4.21)$$

$$\frac{\partial \mathcal{L}}{\partial q^n} : f_1 MRS_{h,c} = \pi \quad (4.22)$$

$$\frac{\partial \mathcal{L}}{\partial e} : f_2 q_e^r MRS_{h,c} = -MRS_{p,c} \quad (4.23)$$

Equations (4.19),(4.20) and (4.21) determine all optimal time decisions. Like in any other traditional labor supply model, optimal leisure is given by the equality of the market wage rate and the marginal rate of substitution between leisure and consumption (Equation (4.19)).

Equation (4.20) explains the decision to use the free services from the CDC. Possible marginal benefits are on the left hand side of the inequality. Marginal costs are on the right hand side. The effect of one additional hour at the CDC on the child's human capital will depend on the quality gap between maternal and CDC care, which is equal to $f_1 q^t - f_2 q^r$. The first term ($f_1 q^t$) measures the raw marginal effect of CDC time on the child's human capital, but such an event implies that the child spent one less hour with her mother. Therefore, we must subtract the marginal effect of maternal time on the child's human capital ($f_2 q^r$) to determine the final effect. Notice that the quality gap could be either positive or negative, and it is valued by the mother using her marginal rate of substitution between human capital and consumption ($MRS_{h,c}$). Use of services from the CDC also imply that the mother could work additional hours paid at the market wage rate w . Increasing CDC use also implies less total parental effort (er) needs to be exerted and, so, it can provide some relief from parenting effort. This possible relief is valued using the marginal rate of substitution between parental effort and consumption ($MRS_{p,c}$). Although the CDC offers a free service, there may be an implicit cost generated by participation stigma or by

associated logistical challenges. This cost is captured by the marginal rate of substitution between time spent at the CDC and consumption ($MRS_{t,c}$).

Optimal non-maternal and non-CDC care time is given by equation (4.21). Note its similarity with the decision rule for use of CDC services. In this case, what matters is the quality gap between other caregivers and maternal care, $f_1q^n - f_2q^r$. Another difference lies in the financial expenditure measured by πq^n .

Recall that quality of care is endogenous in this model. Quality of non-maternal, non-CDC care (q^n) is determined by equation (4.22). Equation (4.23) explains the decision of optimal parenting effort (e), which is the key choice behind quality of maternal care (q^r). In both cases, the marginal return to additional quality depends on the human capital technology. The marginal productivity of non-maternal care (f_1) measures the benefits of additional quality from this type of caregiver. Extra maternal effort translates into additional human capital in the child depending on the marginal productivity of maternal care ($f_2 q_e^r$). Both marginal effects must be valued using the marginal rate of substitution between the child's human capital and consumption ($MRS_{h,c}$). Recall that π is the price of one unit of effective care by a caregiver different than the mother or the CDC. The implicit price of maternal effort is measured using the marginal rate of substitution between parental effort and consumption ($MRS_{p,c}$).

What do these conditions suggest about the key drivers of the decision of how many hours of free CDC care to take-up and how to adjust on other margins? First, potential wage (w) is key as both a proxy for the value of an extra hour doing something besides maternal care and, if productivity in the labor market and in parenting are correlated, also for differences in the productivity of maternal-care time (f_2q^r). Potential wage influences the CDC take-up decision problem in countervailing ways. On one hand, a higher wage increases the potential consumption or leisure benefit of the freed up maternal hour and would encourage take up through this channel. On the other hand, a higher wage may imply that each hour of maternal care is potentially more-productive and shrink the child-

development benefit of CDC use by making the quality-gap smaller, consistent with the findings of [Bernal and Keane \(2011\)](#). Second, differences in the ways that parents balance competing priorities against the costs of investment in child skill ($MRS_{h,c}$; $MRS_{p,c}$) may help explain they make different take-up choices. Finally, the productivity of postnatal investments (f_1 , f_2) in producing child skill may depend on the child condition at birth and the endowment shock that the child experienced.

Factors that the model identifies as driving postnatal investment decisions inform our analysis of the IHDP data. Unlike family income, these three factors are fixed at the time of the child’s birth, which is also the time of random assignment to treatment. We study heterogeneity in treatment effects along these dimensions on numerous postnatal choices that mothers make that influence child development: maternal care quantity and quality, non-maternal care quality and quantity, maternal market-labor hours, and maternal leisure hours.

4.3 Data and Variables

4.3.1 Factors Examined for Heterogeneity in Effects: Potential Wage (\hat{w}), pre-natal investment level (I_0^*), and child’s endowment (ϕ)

The IHDP contains many variables that should be informative about potential wage, pre-natal investment, and child’s endowment but not direct measurement of these factors alone. We harness outside information to develop measures of each variable of interest for each individual in the IHDP. The basic approach is to estimate a model in the outside dataset and then score each IHDP observation using the model’s estimated parameters. That is, we impute conditional means in place of missing values.⁵

⁵This is different than mean-imputation or multiple-imputation as usually practiced. Usually, the problem is that, within a single dataset, a variable (x) has some individuals with observed values and other individuals with missing values. Let z indicate whether the value is observed for each individual. Typically, other variables (d) have fully-observed values. In this case, researchers often model the relationship between

Potential Wage (\hat{w})

Rather than focusing on income, which combines wage, hours of work, and non-labor sources of income, the present study focuses on differences in effects based on mother’s potential wage as predicted by characteristics fixed at the time of random assignment. Potential wage ties directly to economic tradeoffs mothers face in how they use their time.

We assume that potential wage depends on observed and unobserved maternal characteristics. Using a Heckman selection model estimated in a similar Current Population Survey sample, based on variables available in both the CPS and IHDP, we obtain the expected potential wage, $\hat{w}(m)$, for a mother with a given set of observables (m).

We use the Current Population Survey March supplements for 1986-89 from MPC-IPUMS (Flood et al., 2015). We limit the sample to mothers between the ages of 15 and 55 with at least one child below the age of 5, excluding non-civilians, unpaid family workers, and the self-employed. In terms of cleaning and modeling, we largely follow Mulligan and Rubinstein (2008). However, we include women of color and allow wage offers and employment probabilities to differ by ethnicity. Observed hourly wage is the ratio of last year’s total labor income divided by usual hours per week times weeks worked. Wages below \$3.73 and above \$80 in 2012 dollars are trimmed.

The mothers who participated in the IHDP are not a representative sample for the United States. They have different demographic and socioeconomic profiles, when compared to the rest of the country. As evidence consider Table 4.2 , which compares basic

the variable with some missing values and the variables with fully-observed values in the subsample where x is observed ($z=1$). Then, the subsample where x is missing ($z=0$) are scored and this is used to impute missing values and the primary relationship of interest, $E[y|x]$, is then estimated using the full sample. While this can produce unbiased estimates under some conditions, the conditions are often not credible. Some selection process drove some individuals to have missing values and others to have observed values. This selection process might also affect the primary relationship of interest and lead to bias. Our situation is different. Here, all individuals have missing data on the variables in question. There is no selection into observability. The original IHDP researchers collected data on a huge number of variables but missed a few specific variables that we care about. We are harnessing the outside data to understand the relationship between observables in both datasets and the missing variables of interest. Then, we use the conditional mean prediction as an imputed proxy for the missing values.

characteristics from the IHDP and the CPS samples. Around 80% of the women included in the CPS were married; this was the case for only 46% of the women in the IHDP sample. Most of the mothers in the CPS sample were Non-Hispanic Whites (70 %), whereas most of the IHDP mothers were African American (52%). The IHDP participants also had, on average, less schooling and less potential experience in the labor market.

We use a standard Heckman model of selection into the workforce ($L=1$) estimated by the 2-step method (Heckman, 1974):

$$\ln(w) = X\beta^w + \theta^w \lambda(Z\delta^w) + \epsilon^w \quad (4.24)$$

$$\Pr(L = 1 | Z) = \Phi(Z\delta^w) \quad (4.25)$$

Wage determinants (X) are potential work experience, indicators of educational attainment, ethnicity, and marital status.⁶ To capture differences in local-market conditions, we include an indicator for residence in each of the 8 IHDP site's metropolitan areas, an indicator for other SMSA residency and indicators for region and year.

The participation determinants (Z) include all components of X as well as the following variables, which are excluded from the wage equation: number of children below age 5, age of the youngest child and number of other children in household.⁷ The Heckman selection model produces estimates for β^w , δ^w and θ^w , which are reported in Table 4.3 . The first column corresponds to the wage equation and the second column reports the

⁶Potential work experience is defined as age - years of completed schooling - 6. All the way up to quartic term is included, in addition to interactions with education attainment indicators. Less than high school; high school only (women who finished 12th grade, have a high school diploma or equivalent); some college (between one and three years of college education); college graduate (four or more years of college education). High school only is the omitted category. Non-Hispanic Whites; African-American; Hispanic; Other. Non-Hispanic White is the omitted category. Never-married; Married; Separated / Widowed / Divorced. Married is the omitted category.

⁷We also include the interaction of these three variables with the marital status indicators. Observations that are missing any demographic variables are dropped.

selection equation. The results from the Heckit model are sensible and consistent with the literature.⁸ These estimates are used to predict an expected potential wage for each mother in the IHDP sample, treating the estimates as known parameters.⁹ The first rows of Table 4.2 summarize the results. The average potential wage for working mothers in the CPS sample is equal to \$13.46 per hour, whereas it is \$8.08 for working mothers and \$6.62 for all mothers in the IHDP.¹⁰

Pre-natal Investment (I_0^*) and Child's Endowment (ϕ)

To separately measure two key determinants of birth conditions, prenatal investment levels and child endowment, we characterize the IHDP sample in the national distribution by drawing on data from the ECLS-B while controlling for common demographic determinants of birth conditions. To capture this relationship, we assume that a prenatal production function maps observed maternal characteristics that would influence fetal development and maternal beliefs (X), latent prenatal investments (I_0^*), and the child's idiosyncratic endowment (ϕ) into h_0 . Assume the function is linear,

$$h_0 \equiv \pi_0 + \pi_1 I_0^* + \pi_2 X + \phi \tag{4.26}$$

Also, assume ϕ is mean independent of I_0^* , conditional on X . This assumption is credible given that I_0^* is chosen pre-natally, before information about child endowment ϕ is known to the mother (Aizer and Cunha, 2012).

⁸Potential experience and having a college degree increase the probability of working and rise the potential wage. The number of children under the age of 5 reduces the probability of working for wages. The number of children in the household who are older than 5 years also reduced the probability, but by about half as much. Most importantly, the inverse Mills ratio (Lamda) has a significant negative coefficient, suggesting it is correcting for selection into the labor force.

⁹We exclude geographic variables when scoring the IHDP sample in order to focus the variation in potential wage on human capital and family, rather than cross-site differences in cost of living and wage levels. We include site dummies in all outcome models. We follow Cameron and Trivedi (2010), pp. 562 - 565, on how to calculate the predicted value from a selection model in which the outcome of interest is in logs.

¹⁰ $\log(13.46) = 2.60$

We seek to understand these relationships in the Early Childhood Longitudinal Study – Birth cohort (ECLS-B), the nation’s first nationally-representative birth cohort consisting of approximately 14,000 children born in 2001 (Nord et al., 2006).¹¹ To approximate (I_0^*, ϕ) , we proxy h_0 with the two birth outcomes on which the IHDP sample is selected: weight (W) and gestational age (A). In a SUR framework, we regress each of these birth outcomes on a vector of observable pre-natal investment choices (C_0) and on maternal and child characteristics (X).

$$\begin{pmatrix} W \\ A \end{pmatrix} = \begin{pmatrix} \pi_0^W \\ \pi_0^A \end{pmatrix} + \begin{pmatrix} \pi_1^W \\ \pi_1^A \end{pmatrix} C_0 + \begin{pmatrix} \pi_2^W \\ \pi_2^A \end{pmatrix} X + \begin{pmatrix} \phi_W \\ \phi_A \end{pmatrix} \quad (4.27)$$

Given our strategy, we limit the analysis to variables that are available in both the IHDP and ECLS-B. C_0 includes average number of cigarettes smoked per day during pregnancy, average number of alcoholic drinks consumed per week during pregnancy, an indicator of drug use, maternal weight gain during pregnancy, trimester of first pre-natal care and an indicator if no prenatal care services were used. The measures of X are ethnicity, marital status, mother’s schooling and age at child’s birth, mother’s parity, indicator for non-singleton pregnancy and indicator for female baby. Table 4.4 provides summary statistics from the ECLS-B and IHDP samples on these variables. Estimating the SUR model in the ECLS-B produces estimates for $(\pi_0^W, \pi_1^W, \pi_2^W, \pi_0^A, \pi_1^A, \pi_2^A)$, which are available in Table 4.5

Using the coefficients estimated through the SUR model, we generate a vector of estimates, for each observation in the ECLS-B and each birth outcome: $[\hat{\pi}_1^k C_0; \hat{\pi}_0^k + \hat{\pi}_2^k X; \hat{\phi}_k]_{k=W,A}$. The first term, $\hat{\pi}_1^k C_0$, measures the pre-natal investment level chosen by the mother, in units of the corresponding dependent variable (kilograms if $k = W$, or weeks if $k = A$). The second term, $\hat{\pi}_0^k + \hat{\pi}_2^k X$, captures the predicted birth outcome associated with a particular

¹¹Because the IHDP sample is selected on explicit thresholds for birth weight and gestational age, studying the relationship between I_0^* and h_0 in the IHDP sample directly would produce misleading conclusions.

maternal type (X), holding pre-natal investment choices fixed. The third term corresponds to the residual, $\hat{\phi}_k = k - \hat{\pi}_1^k C_0 - \hat{\pi}_0^k - \hat{\pi}_2^k X$, which we will use as a noisy measure of the child's endowment.¹²

The distribution of $\hat{\pi}_1^k C_0$ in the ECLS-B is nationally representative. It measures the distribution of pre-natal investments that affect birth outcomes comparing among mothers of the same type (X). We have two distributions, each one based on a different birth outcome ($\hat{\pi}_1^W C_0$ and $\hat{\pi}_1^A C_0$). We record the percentiles of each distribution, its mean and standard deviation, and transform each individual's measure to a z-score. Next, we average the z-scores of pre-natal investment levels for each individual across birth weight and gestational age. We standardize the new average so that it has mean 0 and standard deviation 1.¹³ This is our final proxy for pre-natal investment, I_0^* . The distribution of I_0^* in the ECLS-B is available in panel a of Figure 4.1. In addition, we use the same scoring procedure for each member of the IHDP sample. This delivers a measure of I_0^* in the IHDP, which is measured with respect to the national norm. The result can be observed in panel b of Figure 4.1. Note that the distribution of pre-natal investment among IHDP mothers is slightly shifted to the left, when compared to the ECLS-B distribution.

Finally, we follow a similar procedure to create a measure of the child's endowment. We average the standardized birth weight and gestational age residuals within the ECLS-B ($\hat{\phi}_W$ and $\hat{\phi}_A$). We standardized this new average again to create a nationally representative distribution of endowments (Panel c in Figure 4.1). We then use the same scoring steps with the IHDP sample. The result is our proxy for ϕ and its distribution can be seen in panel d of Figure 4.1. Note the strong difference in the endowment distribution of IHDP participants and the national distribution: children selected into the IHDP had very negative endowment shocks.

¹²We do not use the second term elsewhere. It provides a different characterization of maternal type that summarized many demographic and family characteristics according to the roles in birth-condition determination. We prefer to focus on potential wage, which does a similar thing but in a way more directly relevant to postnatal economic choices.

¹³This ensures the two outcomes receive equal weight, even though they are measured in different units.

In general, children in the IHDP received strongly negative endowment shocks when compared to the distribution of shocks in the nationally representative ECLS-B sample.¹⁴ The IHDP sample’s average percentile of child endowment is the 5th percentile. The median percentile is the 3rd and the average z-score is -2.4. Mothers in the IHDP tend to make lower levels of pre-natal investment than observationally similar mothers in the national population. The average pre-natal investment percentile is the 27th percentile. The median percentile is 19 and the average z-score is -0.85. The main factor driving selection into the IHDP sample appears to be extreme negative realizations of children’s endowments rather than low levels of prenatal investment.

4.3.2 Measures of Postnatal Choices

We will look at heterogeneous IHDP-treatment effects on a variety of outcomes that reflect post-natal choices. These include both child-development outcomes and parental choices about allocation of time and money on inputs that affect child development and other uses. This section introduces the measures of these outcomes.

Table 4.6 presents summary statistics for all the variables in the main analysis. The primary outcome is child cognitive skill (h) at the end of the intervention as measured by Stanford Binet IQ at 36 months (all ages are chronologically corrected, based on due date). Average IQ in the sample (88.4) is almost a standard deviation (15) below the national norm (100).

Inputs into the production function should reflect maternal and non-maternal effective units of care during the first three years of life. Hours per week of maternal care (r) correspond to the average of maternal self-reported hours in the 18-month and 30-month family interviews. Hours of care at the CDCs (t) come from administrative data and are the average weekly attendance over the 2 years it was offered. Hours of care with other care

¹⁴Appendix A8 contains details about how these variables are measured.

takers is calculated as a residual, using the child’s time constraint ($n = T_c - r - t$).¹⁵

We make a clear distinction between quantity (r) and quality (q^r) of maternal care. To measure quality, we use the Learning and Literacy component from the Infant-Toddler Home Environment score, which is assumed to be affected by maternal effort oriented towards building cognitive capacity in her child (Linver, Martin, and Brooks-Gunn, 2004; Fuligni, Han, and Brooks-Gunn, 2004). The IHDP gathered data for the Home Environment scores at 12-month and 36-months. Table 4.7 presents the yes-or-no questions available in the data. We created a quality index by performing factor analysis on the tetrachoric correlation matrix across items at each age. The values reported for q^r in Table 4.6 correspond to the standardized quality index at 36 months. So, the units of q^r are standard deviations within the IHDP sample.

We do not directly observe the quality of nonmaternal care (q^n) in the IHDP. To measure it, we combine IHDP data on child and family characteristics and on the chosen nonmaternal care settings – partner, sibling, grandmother, another relative, babysitter, day care home, day care center, someone else and the child’s father, if he lives in another home – with data from the National Institute of Child Health and Human Development’s Study of Early Child Care and Youth Development (SECCYD) on similar variables and care quality. We use models of nonmaternal care quality estimated in the SECCYD based on these predictors and then score the IHDP sample using the SECCYD-derived estimates to proxy for q^n . We calibrate the hourly price of nonmaternal care (π) and the scale of q^n using contemporaneous survey data on prices (Kisker et al., 1991). Details are in Appendix A8.

¹⁵We suppose $T_c = 87.5$ hours per week. Based on Iglowstein et al. (2003), p. 304, average night time sleep duration for 2 year olds is approximately 11.5 hours. Therefore, the average child would require $(24 - 11.5) \times 7$ hours of direct care per week.

4.4 Results

Participants in the IHDP were randomly assigned either to the treatment- or control-group. As a consequence, we can study the heterogeneity in reduced-form treatment effects using a standard regression framework. We present main results in tables 4.8 and 4.9. These tables explore the short-term and long-term treatment effects of the IHDP intervention on cognitive development (Table 4.8), as well as the effect on all the inputs up to age 36 months which determine cognitive development (Table 4.9). In order to capture treatment heterogeneity, we split the sample using thresholds of potential wage and prenatal investment. We define low-wage (high-wage) mothers as those with a potential wage below (above) the 33rd percentile of the distribution within the sample and capture this in an indicator variable. In a similar way, mothers whose level of prenatal investment is below (above) the sample's 33rd percentile belong to the low (high) prenatal investment category. In these analyses, we also control for main effects of child endowment and site.

To explore robustness to this functional form assumption, we allow a different characterization of the relationships. We consider four dimensions of possible heterogeneity: child birthweight, mother's expected potential wage (\hat{w}), pre-natal investment levels that affect the child's condition at birth (I_0^*) estimated after conditionally controlling for many observable characteristics of the family, mother and pregnancy, and, lastly, the child's endowment (ϕ), which measures how that child's condition at birth in the national distribution of children from observably-similar families who made observably-similar prenatal investment choices. For each of four dimensions of possible heterogeneity (x), we estimate a separate regression:

$$y = \beta_0 + \beta_1 T + \beta_2 x + \beta_3 T x + \beta_4 x^2 + \beta_5 T x^2 + \delta \mathbb{I}[\text{site}] + \varepsilon \quad (4.28)$$

where y represents an outcome of interest, T is an IHDP-treatment indicator, x is the

variable along which we want to measure differences in the treatment effect, and δ controls for site. Interaction with a quadratic of x allows treatment effects to vary non-linearly with x . The treatment effect, as a function of x , is equal to:

$$E[y|x, T = 1] - E[y|x, T = 0] = \beta_1 + \beta_3x + \beta_5x^2 \quad (4.29)$$

The prior literature has found substantial differences in the IHDP’s treatment effect across birth weights, usually with smaller effects at lower birth weights. However, as noted earlier, differences in birth weight reflect a combination in differences in family type, prenatal investment choices that may be reflect differences in parental preferences, and differences in other factors. The present study aims to unpack the heterogeneous effects by birth weight. To communicate the results clearly, we plot the estimated treatment effect and 95 percent confidence intervals at different values of the four dimensions of heterogeneity. Results are summarized in figures 4.2 through 4.10. Each figure corresponds to an outcome and its four panels plot the treatment effect across different values of birth weight, potential wage, pre-natal investment, and child endowment.¹⁶

Cognitive and behavioral outcomes

We begin by unpacking the known result that treatment effects on 36-month IQ were larger for children born weighing 2,000 - 2,500 grams (high low birth weight) than those born at lower weight (low low birth weight). Figure 4.2 plots the predicted IQ level for each birthweight and treatment group based on the empirical model above along with 95 percent confidence intervals. In the control-group, predicted IQ increases in birthweight up to about 1,500 grams and flattens out across higher weights. In contrast, in the treatment-group, predicted IQ starts off a bit flat and then increases with birthweight across the whole range above 1,000 grams.

¹⁶Each of the regressions is separate. For instance, we do not control for the endowment when estimating the treatment effects by mother’s potential wage. This current structure seems to provide the most transparent interpretation.

This generates the result that treatment effect increases in birthweight. The first panel of Figure 4.3 displays the estimated treatment effect by birthweight along with 95 percent confidence intervals. There is strong evidence of a positive effect on IQ at 36 months, especially for those born at weights above 1,500 g. For children born lighter, there is more variance in outcomes and the estimated treatment effect is positive but estimates are noisier

In the second panel of Figure 4.2, we see that potential wage is a strong predictor of child IQ in both the treatment and control groups. However, the treatment boosts IQ for children of low-wage, but not high-wage, mothers (second panel of Figure 4.3). Among children of mothers with low- and mid-levels of potential wage, the treatment effect is large and precisely estimated. They gained around two-thirds of a standard deviation (10 points) of IQ. At higher levels of potential wage, the effect diminishes and becomes null.

These conclusions are consistent with the regression results presented in Table 4.8. Each column represents a different outcome: nationally-normed standardized IQ at various ages. For each outcome, the same specification is used. This specification is designed to test for heterogeneity in treatment effects by potential wage and prenatal investment level. Column 1 explores the effects on IQ at 36 months. The 0.733 (s.e. 0.0897) estimated effect of the treatment indicator measures the average treatment effect in the omitted category: children of mothers with low potential wage and low levels of prenatal investment. The 0.528 (s.e. 0.130) estimated coefficient on the indicator of higher-potential wage picks up the average difference between children of low- and higher-potential wage mothers in the control group. In a sense, this measures the socioeconomic status (SES)-based gap in cognitive skill. Echoing Duncan and Sojourner (2013)'s finding based on family income, the treatment more than closed the SES gap at age-3.¹⁷ The -0.265 (s.e. 0.126) estimated coefficient on the interaction between treatment and the higher-potential-wage indicator expresses the fact that the treatment impact was larger among children whose families faced tighter economic constraints (less impactful among children whose mothers had higher earning power).

¹⁷Duncan and Sojourner (2013) excluded children born low, low-birth weight. This analysis does not.

The 0.268 (s.e. 0.0605) estimated coefficient on the higher-prenatal-investment indicator has a sensible sign and strong effect. In the control-group, those who received higher levels of prenatal investment scored about a quarter of a standard deviation higher on IQ than those who received low levels of prenatal investment. This could be due to both prenatal investment and correlated postnatal investments. The 0.0801 (0.0989) estimated coefficient on the interaction between treatment and the indicator of higher prenatal investment suggests that there was not significant heterogeneity in this dimension. The main effect of endowment percentile is not significant. Site dummies are included but not reported.

The remaining three columns capture the long-term effects on cognitive development at 5, 8 and 18 years of age. Potential wage is a strong predictor of IQ at every age. On average, children of mothers whose potential wage is above the 33rd percentile have an IQ which is 0.4 to 0.8 s.d. higher than the IQ of children in the low potential-wage group in the control group. In addition, the treatment effect fades down as children age. Most importantly, through age-8, the treatment effect is about 0.3 s.d. lower among children whose mothers have higher potential wages than among children whose mothers have low potential wages. This is evidence that the IHDP's treatment effects differ depending on mothers' potential wage, at least through age 8. The interaction is not significant at age 18 although about a third of the sample has attrited then.¹⁸

Consider now prenatal investment. There is a strong and persistent gap in cognitive development, depending on how much parents invested during the prenatal period. We estimate there is a stable advantage of approximately a third of a standard deviation on IQ if parents' prenatal investment decisions locate them above the 33rd percentile of the within sample distribution. This gap is found at every age, even at 18 years old. Finally, we found no heterogeneity on treatment effect between low- and high-levels of prenatal investment.

Return now to Figures 4.2 and 4.3. The graphs are consistent with the regressions

¹⁸Figures presenting heterogeneous treatment effects on IQ at each age allowing for quadratic interactions in each dimension are presented in Appendix Figures A1 to A3

results: the treatment group’s predicted IQ is higher across the range of prenatal investment levels (panel three in Figure 4.2), but the estimated treatment effect is relatively constant across this range, with weak evidence of a small decline at high levels of prenatal investment (panel three in Figure 4.3). The fourth panel shows little relationship between the residual determinants of birth weight, that is child endowment, and the predicted IQ levels in either treatment group or the treatment effects.

Time allocation

Any effect of the IHDP treatment on child development cannot be interpreted simply as the effect of time spent at the high-quality centers available for families in the treatment group. Households react to the intervention by reallocating various resources, thus providing the child with a new combination of maternal and nonmaternal care inputs. For instance, any hour the child spends in a center is an hour the child does not spend in an alternative setting, such as in maternal care or market-based care. Any reduction in the hours of maternal care may provide relief that allows mothers to provide higher-quality of care in the (fewer) hours they provide care. The maternal hours freed up could be allocated to additional market labor or to other activities (called leisure here, but potentially including care of other children and a wide variety of alternative activities). This section describes evidence on reallocations in response to the IHDP’s offer and how this response varies across different types of families.

Although children could use the services from the CDCs for up to 40 hours per week, average take-up in the treatment group was only about 16 hours. There were no substantial differences in take-up depending on child birthweight or prenatal investment level (Figure 4.4). Additional evidence of average take-up can be found on the first column of Table 4.9.

Heterogeneity by mother’s potential wage reveals evidence of a non-monotone relationship. In the control group, no one could take up any hours. In the treatment group, mothers with the lowest and highest potential wages take up less hours than mothers with mid-range

potential wages. Mothers with the lowest potential wages used about 15 hours per week of CDC care, those with wages of \$10 per hour used about 17 hours per week, and those with a \$21 potential wage used the CDC for just 7 hours per week.

Mothers who chose different levels of prenatal investment did not choose to take up significantly different amounts of CDC care. This is remarkable because it suggests that differences in maternal tastes did not drive differences in the take-up of the free service. The IHDP's offer of free transportation to and from the CDCs may have helped ensure that transportation-cost frictions did not create a channel for differences in maternal tastes to drive differences in CDC take up.

The strongest dimension of heterogeneity is that parents of children with lower endowments (born in worse-than-expected condition given their background and prenatal investment levels) took up significantly fewer CDC hours on average. Those in the lowest percentile of the national endowment distribution took up an average of 15 hours of CDC care per week, while those in the 40th percentile of the national endowment distribution took up just over 20 hours (fourth panel in Figure 4.4). The first column of Table 4.9 also presents evidence of the positive correlation between the child's endowment and the average number of hours the child spent at the CDC.

As reflected by the child's time constraint, use of the CDC must substitute for either maternal care or other non-maternal care. To explore these patterns of substitution, consider figure 4.5, figure 4.6 and the second and third columns from Table 4.9. Figure 4.5 measures the treatment effect on hours of non-CDC, non-maternal care (n); figure 4.6 does the same for hours of maternal care (r). The opportunity cost of mother's time appears to be a fundamental driver in both cases, because the kinds of care that CDC hours substitute for varies substantially by maternal potential wage. First, consider the reaction of mothers with the highest potential wages. The treatment induced them to reduce the number of hours of other sources of non-maternal care by almost 17 hours per week and produced a barely significant effect on the number of hours of maternal care. Mothers with high

potential wages tended to use the nonmaternal CDC services as a substitute for other non-maternal care sources rather than as a substitute for maternal care time. Mothers with low potential wages followed the opposite pattern of substitution. Treatment led them to reduce maternal-care time by 11 hours per week on average while reducing the number of hours of non-maternal care by only a small amount (approximately 5 hours per week). This substitution pattern can also be found on columns 2 and 3 of Table 4.9. Note the negative treatment effect of the IHDP intervention on hours of non-maternal care (4.7 hours per week) and hours of maternal care (11.9 hours per week) representing the effects in the low potential-wage, low prenatal investment omitted group. However, the negative treatment effect on hours of *non-maternal* care is even larger for those mother's whose potential wage is *above* the 33rd percentile. In contrast, the negative treatment effect on *maternal* care time is larger for the opposite group, mothers whose opportunity cost of time is *below* the 33rd percentile of the sample distribution.

Recall that parents of children with lower endowments took up about 5 hours less CDC care weekly on average. This largely crowded out other forms of nonmaternal care and did not reduce maternal-care hours. Finally, no heterogeneity by prenatal investment levels is evident.

In conclusion, the allocation of child time among different caregivers, which is a key input into the production function of early skills, depends not just on the number of hours of free service available to all participants but also on the larger choice environment facing the household. The opportunity cost of mother's time is at the core of those decisions.

As reflected in the maternal time budget, any time the child spends in CDC care makes more non-parenting (of that child) time available, which must be divided between hours working for wages in the labor market (L) or allocation of time to leisure (l).¹⁹ Mothers

¹⁹We define "leisure" as a very broad, residual category: it corresponds to any time the mother has left after accounting for time caring for her IHDP-study child (r) and working in the labor market (L). So it includes time spent caring exclusively for any other children, for elders, volunteering, engaged in home production, as well as activities more conventionally considered as leisure such as reading or sleeping.

of the lower birth weight children increased their labor-market hours but we do not see significant heterogeneity in treatment effects across different levels pre-natal investment. However, mothers with a very high potential wage reduced their number of work hours as a consequence of participating in the IHDP intervention (Figure 4.7 and fourth column in Table 4.9).

The allocation of hours to leisure differed considerably across households. Treatment-group mothers gained back some leisure time, except for parents of very low birth weight infants (birth weight of less than 1 kilogram), who increased their labor-market hours. The treatment effect on leisure appears somewhat strongest among low-wage mothers and, weakly, among those who had chosen lower level of prenatal investment (Figure 4.8). However, this does not show up as statistically significant in the regressions where neither interaction term is significant (fifth column in Table 4.9).

Quality of maternal and non-maternal care

Care time is not the only input in the production of early skills; the quality of care also matters. In our framework, mothers can choose the quality of the care they provide, through a combination of their own human capital and an effort choice. Therefore, we expect maternal effort to be sensitive to participation in the IHDP. Figure 4.9 presents the treatment effect on our preferred proxy for the quality of maternal care. It corresponds to the components of the HOME score, at 36 months, which are related to the promotion of learning and literacy (Linver, Martin, and Brooks-Gunn, 2004; Fuligni, Han, and Brooks-Gunn, 2004). The sixth column of Table 4.9 presents the related regression results.

The pattern of results is interesting and important. Our proxy for the quality of maternal care is positively correlated with mothers' potential wage and prenatal investments. Among mothers with low potential wages, the treatment increases the proxy measure of maternal-care quality but the effect decreases with mother's potential wage. According to the regression results, the treatment effect on the quality of maternal care is 0.53 s.d. for

households who belong to the bottom third of the potential wage and prenatal investment distributions. The size of the treatment effect is cut in half among households with higher potential wage (sixth column in Table 4.9).

This pattern of effects on the quality of maternal care is the mirror image of that observed on the quantity of maternal care. For mothers with high potential wages, there is no treatment effect on either maternal-care quantity or quality. In contrast, for mothers with low potential wages, there is a substantial negative effect on maternal-care quantity and a substantial positive effect on maternal-care quality.

Our economic model offers a possible reason why this might be. The model supposes that, for a given person in a given moment, parenting better requires more effort. Also, for a person providing a given level of parenting quality, parenting longer requires more effort. The treatment allowed mothers with low potential wages to reduce the number of hours they provided direct care to the child, while still feeling comfortable that the child would receive high-quality care. Absent the intervention, they could not afford much high-quality, market-based care. Access to this high-quality care environment reduced the number of hours of parenting they did, providing some effort relief for the mothers. This relief created space for them to raise their instantaneous effort levels during the shorter time they provided care, generating higher observed quality of maternal care. This was not the case among high-wage mothers. This drastic difference in the treatment effect on the quality of maternal care could be one of the main reasons behind the heterogeneous treatment effect on cognitive development. We also observe decreasing treatment effects on maternal-care quality by prenatal investment level and by child endowment.

Figure 4.10 presents heterogeneous treatment effects on the quality of nonmaternal, non-CDC care used. The effects are null among mothers with low potential wages and turns slightly negative as wages rise, in the subpopulation where the quantity of such hours declines dramatically (panel 2). A qualitatively similar pattern appears for prenatal investment level in panel 3. Those who chose low levels of prenatal investment do not change

their average nonmaternal care quality, though recall that they do reduce quantity. However, those with high levels of prenatal investment reduce the quality of nonmaternal care they chose, along with the quantity of such care. Such pattern of results is consistent with the last column of Table 4.9.

This kind of effect may be driven by substitution between CDC care and market-based, nonmaternal care. As we posit in our model, CDC care may be a perfect substitute for high-quality market based care. It is possible that someone could offer such a service in the market. Therefore, when families that would otherwise spend a lot of financial resources on high-quality nonmaternal care are offered the chance to get it for free, they do so and they cut back on their financial expenditures on its substitutes.

4.5 Limitations

Our discussion ignores other components of the IHDP treatment beyond the CDCs, such as the offer of weekly home visiting during the child's first year of life. In the literature and in our own work, there is little evidence of treatment effects at age 12 months. Appendix Table A14 uses a parallel structure to Tables 4.8 and 4.9 to assess whether treatment had differential effects on child mental development or on the quality of maternal care at age 12 months, after a year of weekly home visits are offered but before the offer of free CDC care starts. There are no main effects of treatment on either variable and no significant interaction effects. However, as discussed above, after access to the CDC started, large effects became evident. That said, we cannot rule out the possibility that a program that omitted this element of the IHDP treatment would have different effects than those observed.

The sample is composed exclusively of children born low birth weight and premature. Some may have suffered developmental compromise and may be subject to different developmental processes than children born under normal conditions. There are a few points

to make regarding this issue. First, we characterize the sample with respect to the criteria on which they are selected (birth weight and gestational age at birth) within the context of a nationally-representative birth cohort and with respect to the determinants of these selection variables (maternal characteristics, pre-natal investment choices, and child endowment) and we build these differences into our model. Second, even if one is reluctant to generalize outside the sample's support, the estimates are valuable as informative about children born low birth weight and premature. Third, there is no evidence of a break in the relationship between birth weight and cognitive skills at 2,500 grams (Figlio and Guryan, 2014).

We ignore the costs of goods as inputs, aside from measuring the quality of care. We believe this is justified at this very early stage of development, although the cost of goods themselves and their ability to substitute for or complement personal care-giver attention may be more important as children age (Del Boca, Flinn, and Wiswall, 2014).

Our analyses produce unbiased estimates under the assumption that data are missing completely at random. However, this may not be a valid assumption. Future work will assess robustness to alternative assumptions about missing data.

4.6 Conclusion

Each child has only one first 3 years. The quality of the environments they encounter in this “first 1,000 days” has long-term consequences. Policies that seek to improve these environments must be designed in a way that respects parents’ values and constructively loosens the constraints that parents face. The impacts of policies will be determined by the way the distribution of responses that parents choose.

The quality, quantity, and price of the subsidized environment offered are key design variables. Different parents will react to the same offer in different ways partially because

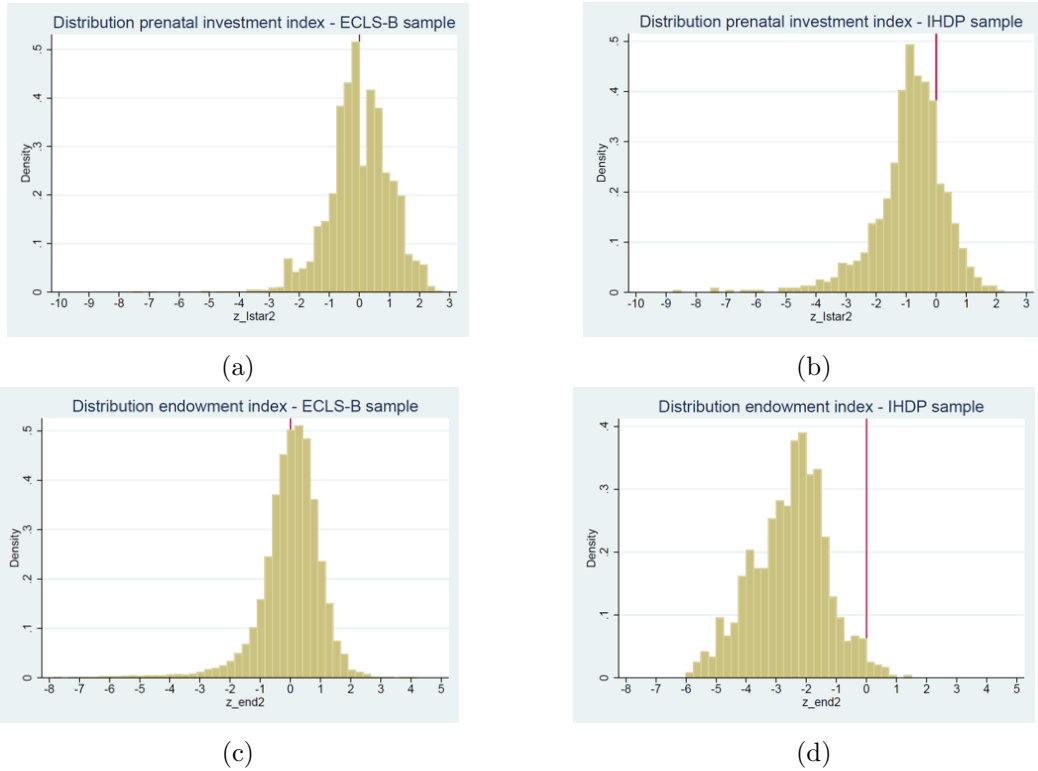
they have different alternatives available. The offer of free, high quality care has large positive effect on the cognitive development of children of mothers with lower potential wages. For these children, access to the CDC triggered increases in hours spent in high-quality nonmaternal care and reductions in maternal-care time while also triggering an increase in the quality of maternal care. In contrast, the effect on children of higher potential wage mothers are different. They take up about the same amount of CDC hours but this crowds out nonmaternal, rather than maternal care, and yields smaller impacts on child skill. This result – differential effects by maternal earning power – echoes earlier findings (Bernal and Keane, 2010; Duncan and Sojourner, 2013) but this paper adds new evidence on mechanisms.

Gelber and Isen (2013) found that parents with kids randomly selected for Head Start eligibility raise the level of parenting quality. They interpret this as evidence of perceived complementarity between parental and non-parental care quality. However, they also recognize that this could be due instead to “changes in parent time with children through impacts on the parents’ time constraint” but lack good measures of parental care quantity to get at this directly. We reproduce their main empirical finding, that low-income parents whose children are eligible for free child care do increase their parenting quality, but we extend the analysis to incorporate a measure of maternal care quantity. We find a decline in maternal care hours for these families. Further, we find that treatment does not reduce maternal care hours or increase parenting quality among higher potential-wage families. This evidence is consistent with our theory that parenting effort matters and that providing access to high-quality nonmaternal care can reduce maternal stress and create the psychic space for parents to parent better.

Intervention programs like the IHDP and some policies, such as Early Head Start and Child Care Assistance Block Grant funding, subsidize child access to nonparental care during this critical developmental period although quality levels tend to be lower than that provided in the IHDP CDCs. Given this offer, parents may take up free, low-quality care

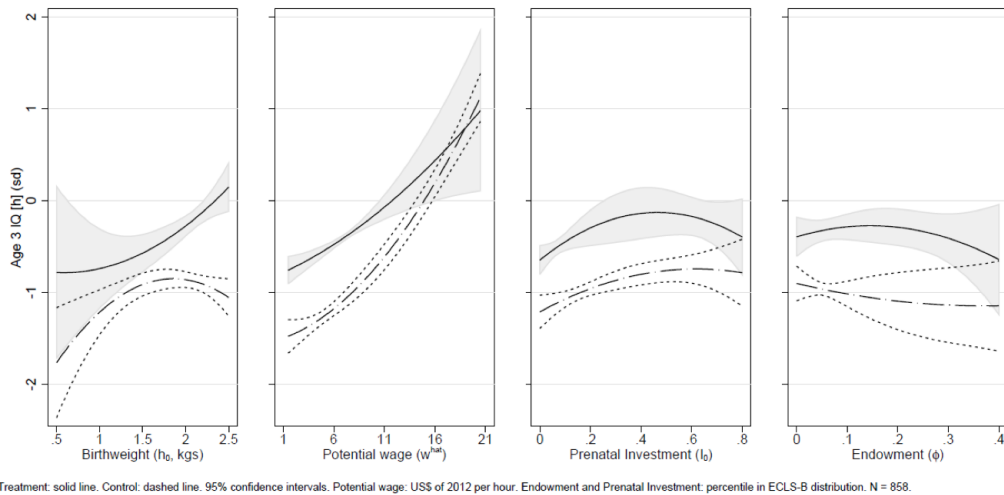
over costly, higher-quality care that they would have provided or purchased themselves (Peltzman, 1973). This could produce negative effects on child skill, though it may increase family income. Future work will estimate a structural model of parents' responses to the IHDP offer and use this as a way of predicting the impacts of child care subsidies with alternative, counter-factual designs, that is alternative combinations of nonparental care quality, quantity, and price.

4.7 Figures



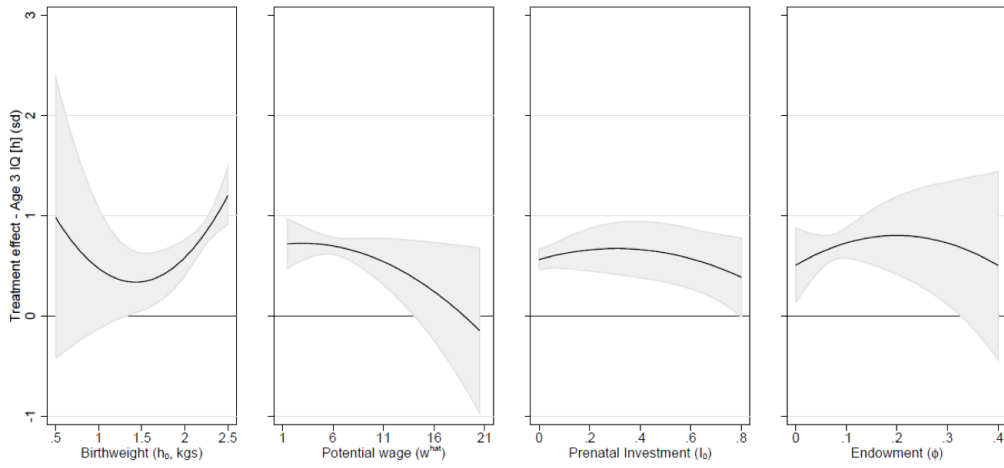
Note: all units are standard deviations from the ECLS-B distribution.

Figure 4.1: Distribution of pre-natal investment and endowment indexes, ECLS-B and IHDP samples



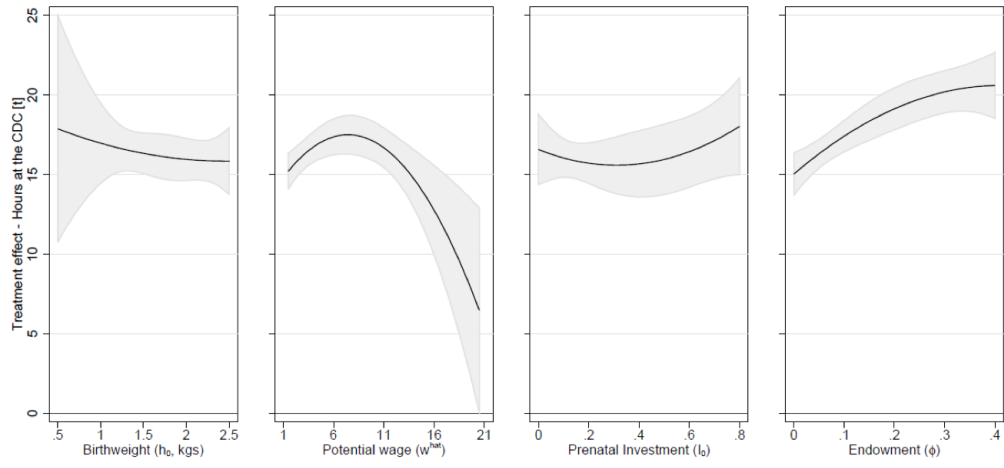
Note: National average = 100; Standard deviation = 16

Figure 4.2: Predicted IQ at 36 months for IHDP treatment and control groups



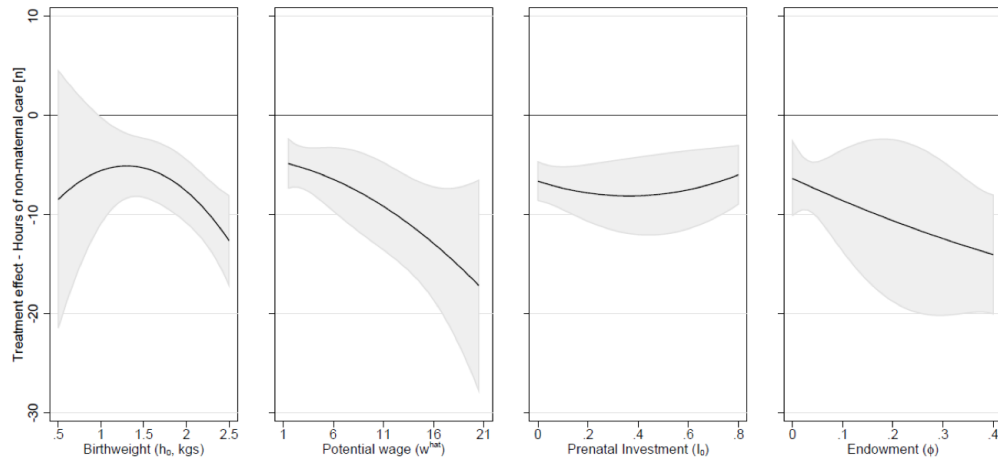
Estimate and 95% confidence interval. Potential wage: US\$ of 2012 per hour. Endowment and Prenatal Investment: percentile in ECLS-B distribution. N = 858.

Figure 4.3: IHDP treatment effects on IQ at 36 months



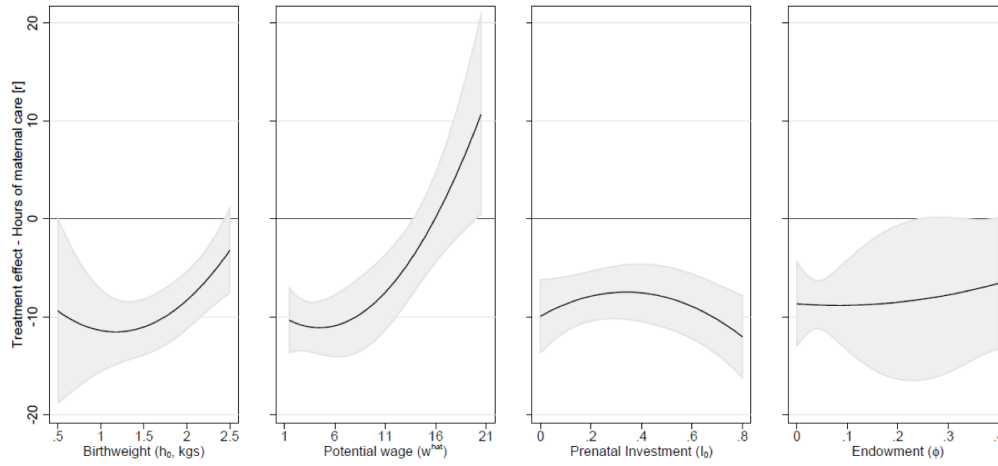
Estimate and 95% confidence interval. Potential wage: US\$ of 2012 per hour. Endowment and Prenatal Investment: percentile in ECLS-B distribution. N = 930.

Figure 4.4: IHDP treatment effects on hours per week of CDC use (*t*)



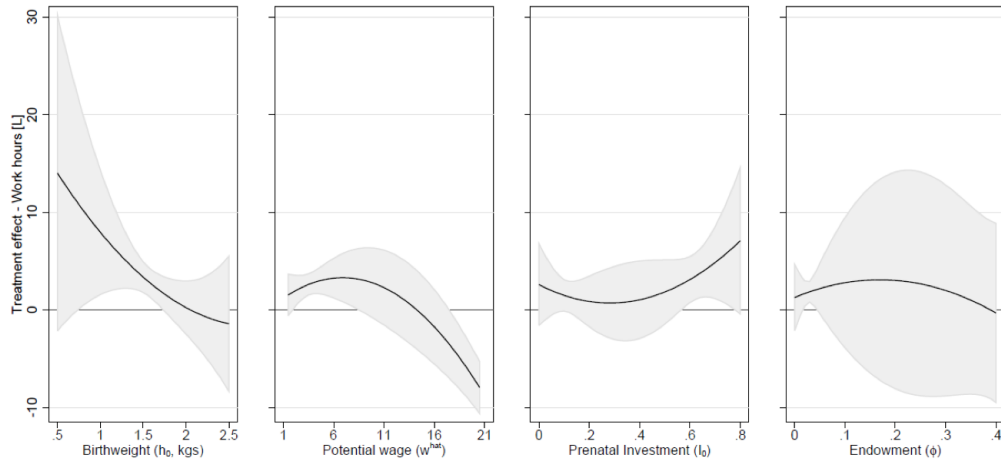
Estimate and 95% confidence interval. Potential wage: US\$ of 2012 per hour. Endowment and Prenatal Investment: percentile in ECLS-B distribution. N = 930.

Figure 4.5: IHDP treatment effects on hours per week of non-maternal care (n)



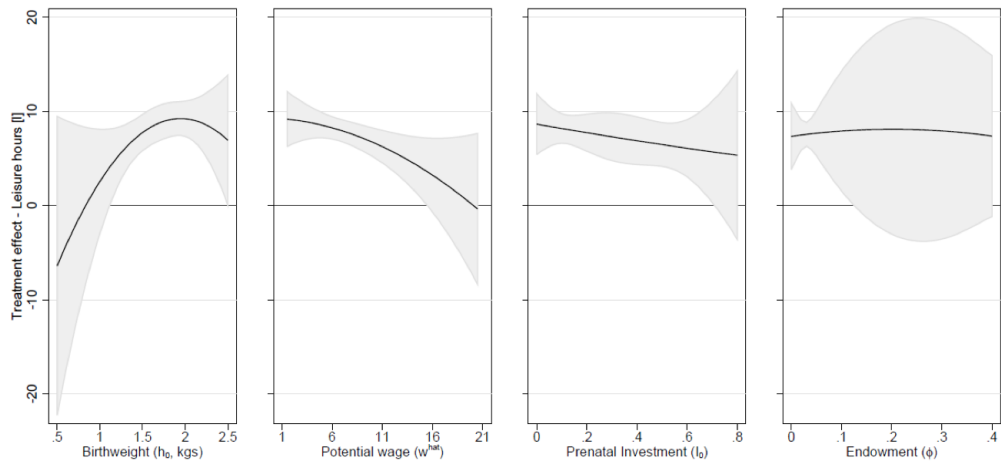
Estimate and 95% confidence interval. Potential wage: US\$ of 2012 per hour. Endowment and Prenatal Investment: percentile in ECLS-B distribution. N = 930.

Figure 4.6: IHDP treatment effects on hours per week of -maternal care (r)



Estimate and 95% confidence interval. Potential wage: US\$ of 2012 per hour. Endowment and Prenatal Investment: percentile in ECLS-B distribution. N = 856.

Figure 4.7: IHDP treatment effects on work hours (L)



Estimate and 95% confidence interval. Potential wage: US\$ of 2012 per hour. Endowment and Prenatal Investment: percentile in ECLS-B distribution. N = 856.

Figure 4.8: IHDP treatment effects on leisure time (l)

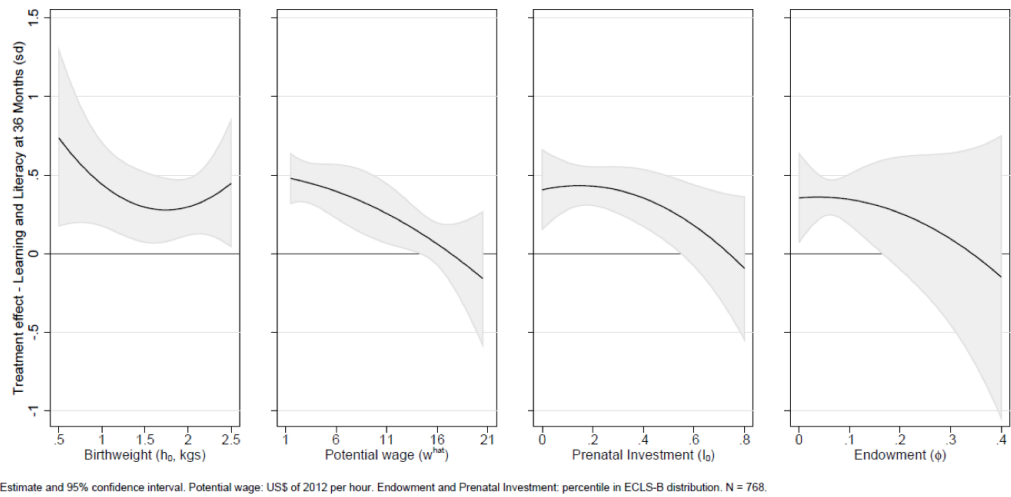


Figure 4.9: IHDP treatment effects on quality of maternal care (q^r)

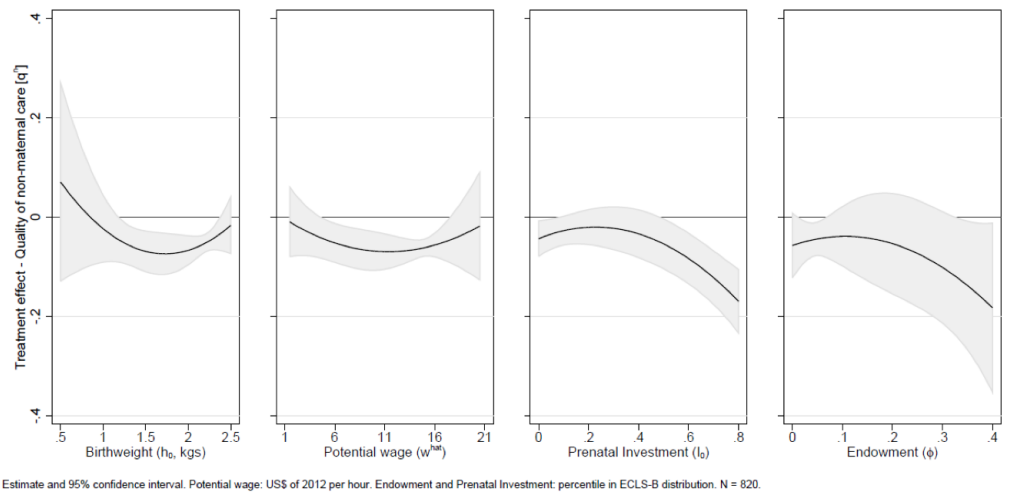


Figure 4.10: IHDP treatment effects on quality of non-maternal care (q^n)

4.8 Tables

		Variables in the model		
	Caretaker	Time with caretaker	Quality of care	Effective units of care provided
Maternal Care	Mother	r	q^r	$q^r r$
Non-maternal care	Free Daycare (CDC)	t	q^t	$q^t t$
	Non-maternal, non-CDC	n	q^n	$q^n n$

Note: total effective units of non-maternal care will be equal to $(q^t t) + (q^n n)$.

Table 4.1: Possible caretakers and effective units of care provided

Continuous variables	CPS			IHDP		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N
Hourly Rate of Pay	2.60	0.56	18,680	2.09	0.71	542
Log, US\$ of 2012	-	-	-	1.89	0.83	985
Worked Indicator	0.60	0.49	30,889	0.52	0.50	913
Potential experience (years)	9.61	5.60	30,889	6.49	5.28	985
Number of own children under age 5	1.30	0.53	30,889	1.50	0.71	985
Age of youngest own child in household	1.75	1.39	30,889	1.70	0.68	985
Number of own children 5y old or older	0.77	1.03	30,889	0.46	0.84	985
Maternal education						
	Share (%)	N		Share (%)	N	
Less than High School	18.4	5,682		40.0	394	
High School graduate	43.7	13,505		27.4	270	
Some College	19.9	6,157		20.0	197	
College graduate	18.0	5,545		12.6	124	
Race and Ethnicity						
	Share (%)	N		Share (%)	N	
Non-Hispanic White	70.4	21,752		33.4	329	
African American	11.0	3,383		52.5	517	
Hispanic	14.6	4,513		10.7	105	
Other	4.0	1,241		3.5	34	
Marital status						
	Share (%)	N		Share (%)	N	
Married	80.8	24,964		46.2	455	
Single	8.6	2,661		45.8	451	
Separated / Divorced / Widowed	10.6	3,264		8.0	79	

CPS Sample: IPUMS-CPS extract, Minnesota Population Center. 1986-89 March Samples. Women, age 15 to 55, with at least one child under the age of 5. Unpaid family workers and self-employed women not included. Hourly Rate of Pay is equal to the ratio of last year's total labor income divided by usual hours per week times weeks worked. Wages below \$3.73 and above \$80 in 2012 dollars are trimmed. IHDP: Infant Health and Development Program sample. Hourly Rate of Pay for the IHDP sample is the predicted value based on the Heckman selection model

Table 4.2: Summary statistics for variables in the potential wage model (\hat{w})

VARIABLES	(1) Ln(hourly wage)	(2) 1 worked
Potential experience	0.0612*** (0.0115)	0.0648*** (0.0233)
Potential experience, squared	-0.00150 (0.00165)	-0.00751** (0.00327)
Potential experience, cubed	-3.10e-05 (8.85e-05)	0.000285* (0.000173)
Potential experience, ^4	1.09e-06 (1.54e-06)	-3.74e-06 (2.96e-06)
Education: Less than High School	0.0981* (0.0541)	-0.759*** (0.0860)
Education: Some College	0.0700 (0.0455)	0.348*** (0.0992)
Education: College degree	0.429*** (0.0540)	0.515*** (0.130)
Experience * Less HS indicator	-0.0493** (0.0198)	0.0592* (0.0337)
Experience * Some Coll. indicator	0.0532** (0.0208)	-0.0773* (0.0448)
Experience * Coll. grad. indicator	0.0249 (0.0253)	-0.0662 (0.0614)
Experience^2 * Less HS indicator	0.00265 (0.00241)	-0.00372 (0.00424)
Experience^2 * Some Coll. indicator	-0.00748** (0.00303)	0.00916 (0.00647)
Experience^2 * Coll. grad. indicator	-0.00423 (0.00389)	0.00521 (0.00967)
Experience^3 * Less HS indicator	-4.75e-05 (0.000113)	0.000113 (0.000204)
Experience^3 * Some Coll. indicator	0.000374** (0.000164)	-0.000382 (0.000352)
Experience^3 * Coll. grad. indicator	0.000228 (0.000229)	-0.000198 (0.000593)
Experience^4 * Less HS indicator	7.21e-09 (1.79e-06)	-8.05e-07 (3.29e-06)
Experience^4 * Some Coll. indicator	-5.74e-06** (2.88e-06)	5.39e-06 (6.26e-06)
Experience^4 * Coll. grad. indicator	-4.47e-06 (4.45e-06)	3.90e-06 (1.23e-05)
Race: African American	-0.0932*** (0.0132)	0.230*** (0.0282)
Race: Hispanic	-0.0712***	-0.0992***

Table 4.3: Estimates from Heckman selection model in CPS sample

	(0.0132)	(0.0247)
Race: Other	-0.0418**	-0.0851**
	(0.0199)	(0.0389)
Marital status: Single	-0.0403**	-0.183**
	(0.0166)	(0.0930)
Marital status: Sep./Div./Wid.	-0.0964***	-0.173*
	(0.0123)	(0.0963)
Number of own children under age 5 in hh		-0.373***
		(0.0168)
Age of youngest own child in household		0.00242
		(0.00680)
Number of own children 5 years old or older		-0.156***
		(0.00936)
Num. of children < 5 * Single indicator		-0.107*
		(0.0566)
Num. of children < 5 * Sep./Div./Wid. indicator		0.0996*
		(0.0531)
Age youngest child * Single indicator		0.0233
		(0.0212)
Age youngest child * Sep./Div./Wid. indicator		0.0987***
		(0.0197)
Num. of children >= 5 * Single indicator		-0.0777**
		(0.0311)
Num. of children >= 5 * Sep./Div./Wid. indicator		-0.0635***
		(0.0230)
Lambda	-0.300***	
	(0.0283)	
Constant	2.218***	0.755***
	(0.0331)	(0.0626)
Observations	30,889	30,889

Note: the selection equation and the wage equation included as additional controls [□] indicators for division (New England, Middle Atlantic, West North Central, South Atlantic, East South Central, West South Central, Mountain and Pacific) and metropolitan area (Boston, MA; Dallas-Forth Worth, TX; Little Rock-North Little Rock, AR; Miami-Hialeah, FL; New Haven-Meriden, CT; New York, NY; Philadelphia, PA/NJ; Seattle-Everett, WA). This additional control are not reported.

Table 4.3: Estimates from Heckman selection model in CPS sample (continued...)

	ECLS-B		IHDP	
	Mean or Percentage	Std. Dev.	Mean or Percentage	Std. Dev.
<i>Conditions at birth</i>				
Birth weight (kg)	3.3	0.6	1.8	0.4
Gestational age (weeks)	38.7	2.4	33.0	2.6
<i>Pre-natal investment choices (C_0)</i>				
Maternal weight gain (kg)	34.9	21.9	23.5	13.0
Cigarettes per day	1.1	4.0	4.3	7.9
Alcoholics drinks per week	0.04	0.3	0.2	0.7
Used drugs (%)	4.3%	-	3.8%	-
Trimester of first prenatal check-up	1.2	0.5	1.3	0.6
No prenatal check-up	0.9%	-	4.5%	-
<i>Child characteristics (X)</i>				
Female	49.0%	-	50.8%	-
Non-singleton fetus	3.1%	-	11.2%	-
African American	15.2%	-	52.4%	-
Hispanic	20.3%	-	10.6%	-
Other ethnicity	6.6%	-	3.4%	-
<i>Mother characteristics (X)</i>				
Parity	2.0	1.1	1.8	1.1
Never married	25.8%	-	45.7%	-
Separated, divorced or widowed	6.7%	-	8.0%	-
Age at birth (years)	28.1	6.1	24.7	6.0
Less than High School	17.6%	-	40%	-
Some College	27.9%	-	20%	-
College graduate	26.0%	-	12.5%	-

ECLS-B: summary statistics based on full sample weights (w1r0).

Table 4.4: Estimates from Heckman selection model in CPS sample

Dependent variable	Birth weight (W)		Gestational age (A)	
	Coefficient	Std. Err.	Coefficient	Std. Err.
	π_1^W		π_1^A	
Maternal weight gain (kg)	10.51	.030	.01	.0001
Maternal weight gain 2	-.04	.0002	-.0000917	8.93e-07
Cigarettes per day	-12.89	.078	-.005	.0003
Alcoholics drinks per week	-60.37	2.310	.16	.010
Alcoholics drinks per week 2	-2.69	.908	-.08	.004
Used drugs (%)	-12.67	1.505	.13	.006
Trimester of first prenatal check-up	-14.99	.602	.06	.002
No prenatal check-up	-60.35	3.245	-.08	.014
	π_2^W		π_2^A	
Child: female	-106.34	.602	.08	.002
Child: non-singleton fetus	-1112.95	1.742	-3.59	.007
Child: African American	-214.45	.972	-.43	.004
Child: Hispanic	-58.80	.839	-.13	.003
Child: Other ethnicity	-118.99	1.239	-.19	.005
Mother: Never married	-38.92	.893	-.10	.003
Mother: Separated, divorced or widowed	-59.00	1.257	-.009	.005
Mother: age at birth (years)	27.87	.453	.06	.001
Mother: age at birth 2	-.44	.007	-.001	.0000334
Mother: Less than High School	-33.94	.955	.03	.004
Mother: Some College	33.44	.834	-.07	.003
Mother: College graduate	28.16	.958	-.01	.004
Parity	96.18	.802	-.04	.003
Parity 2	-9.06	.124	.002	.0005
	π_0^W		π_0^A	
Constant	2659.60	6.658	37.71	.029

Note: SUR model based on ECLS-B full sample weights. The p -value for all coefficients is less than 0.001, except for alcoholic drinks per week (squared term) in the birth-weight equation ($p=0.003$), and the separated, divorced or widowed indicator in the gestational-age equation ($p=0.075$).

Table 4.5: Estimates from SUR model for pre-natal investment using the ECLS-B sample

	Var	Mean	S.D.	Min	Max	N
<i>Child outcomes (standardized)</i>						
Cognitive skill at age 3, Stanford Binet IQ	h	-0.72	1.26	-3.56	2.93	858
Cognitive skill at age 5, WPPSI IQ		-0.54	1.17	-3.73	2.93	758
Cognitive skill at age 8, Wechsler IQ		-0.92	1.84	-6.00	4.60	820
Cognitive skill at age 18, WASI IQ		-0.53	1.08	-3.33	2.20	582
<i>Parental post-natal choices</i>						
Hours per week of maternal care	r	60.95	15.91	12.5	87.5	930
Hours per week at CDC	t	6.15	9.99	0	40.52	930
Hours per week with other caretakers	n	20.39	14.81	0	61	930
Maternal-care quality, Learning and Literacy components of the HOME score at age 3	q^r	0.12	0.98	-1.94	1.49	768
Non-maternal care quality, predicted ORCE	q^n	3.68	0.20	2.87	4.17	820
Hours per week of working time	L	16.56	16.51	0	57	856
Hours per week of leisure	l	92.25	15.94	32	151	856
<i>Characteristics at birth</i>						
Birth weight (kilograms)	h_0	1.80	0.49	0.72	2.5	930
Gestational age at birth (weeks)		33.06	2.59	26	38	930
Expected potential wage, US\$2012 per hour	\hat{w}	8.75	5.73	0.02	23.69	930
Pre-natal investment, percentile	I_0^*	0.27	0.23	0.01	0.93	930
Endowment shock, percentile	ϕ	0.05	0.07	0.01	0.65	930

Table 4.6: Summary statistics

12-month Home Assessment	36-month Home Assessment
At least 10 books are present and visible	Child has toys which teach color, size, shape
Muscle activity toys or equipment	Child has three or more puzzles
Push or pull toys	Child has toys permitting free expression
Parent provides toys for child during visit	Child has toys or games requiring refined movements
Learning equipment appropriate to age: cuddly toys or role playing toys	Child has at least 10 children's books
Learning facilitators: mobile, table and chairs, high chair, play pen	At least 10 books are visible in the apartment
Complex eye-hand coordination toys	Child is encouraged to learn the alphabet
Toys for literature and music	Interior of apartment not dark or perceptually monotonous
Parent reads stories to child at least 3 times weekly	Parent converses with child at least twice during visit
Child has 3 or more books of her own	Child is encouraged to learn spatial relationships
	Child is encouraged to learn to read a few words
	Child has real or toy musical instrument

Based on Linver, Martin and Brooks-Gunn (2004) and Fuligni, Han and Brooks-Gunn (2004).

Table 4.7: Learning an Literacy components (IT-Home score) available in the IHDP sample

		(1)	(2)	(3)	(4)
	Age	36 months (3 years)	5 years	8 years	18 years
	IQ test	Stanford Binet	WPPSI	Wechsler	WASI
Treatment indicator	(T)	0.733*** (0.0897)	0.277* (0.133)	0.366 (0.207)	0.0300 (0.135)
Potential wage above 33 rd percentile	(HW)	0.528*** (0.130)	0.603*** (0.168)	0.797** (0.246)	0.431** (0.150)
Treatment x Potential wage above 33 rd perc.	(T x HW)	-0.265* (0.126)	-0.292* (0.150)	-0.413** (0.148)	-0.0623 (0.0904)
Prenatal Investment above 33 rd percentile	(HI)	0.268*** (0.0605)	0.319** (0.0935)	0.495** (0.178)	0.240*** (0.0643)
Treatment x Prenatal Investment above 33 rd perc.	(T x HI)	0.0801 (0.0989)	-0.0633 (0.0966)	-0.0742 (0.236)	0.0416 (0.127)
Percentile of Endowment		-0.307 (0.347)	-0.746** (0.271)	0.554 (0.594)	0.0142 (0.473)
Constant		-1.321*** (0.118)	-1.298*** (0.139)	-1.994*** (0.164)	-1.260*** (0.128)
Observations		858	758	820	582
R-squared		0.259	0.203	0.176	0.220

Note: The measurement units of all the dependent variables (IQ tests) are standard deviations. T = 1 for individuals included in the treatment group; HW = 1 if the mother's expected potential wage (\hat{w}) is above the 33rd percentile of the distribution within the sample; HI = 1 if the prenatal investment index (I_0^*) is above the 33rd percentile of the distribution within the sample. All regressions include location (site) indicators. Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 4.8: Treatment effect of the IHDP intervention on cognitive development

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Hours per week at the CDC	Hours per week of non-maternal, non-CDC care	Hours per week of maternal care	Work hours per week	Leisure hours per week	Quality of maternal care	Quality of non-maternal care
	t	n	r	L	l	q^r	q^n
Treatment indicator (T)	16.61*** (0.679)	-4.685** (1.751)	-11.93*** (2.252)	3.236*** (0.875)	8.877*** (1.509)	0.529*** (0.0825)	-0.0337 (0.0330)
Potential wage above 33 rd percentile (HW)	0.228 (0.138)	3.171*** (0.751)	-3.399*** (0.666)	9.969*** (2.151)	-5.906** (1.689)	0.644*** (0.175)	0.0993** (0.0367)
Treatment x Potential wage above 33 rd perc. (T x HW)	-0.107 (0.698)	-3.447* (1.485)	3.554** (1.396)	-0.522 (1.637)	-2.301 (1.303)	-0.273* (0.140)	-0.0279 (0.0394)
Prenatal Investment above 33 rd percentile (HI)	0.0611 (0.107)	2.303 (1.839)	-2.364 (1.864)	5.521** (1.852)	-3.891*** (0.701)	0.269*** (0.0532)	0.0578** (0.0205)
Treatment x Prenatal Invest. above 33 rd perc. (T x HI)	-0.592 (1.047)	-0.641 (1.602)	1.233 (1.651)	-1.253 (1.703)	0.134 (1.746)	-0.00470 (0.144)	0.00700 (0.0334)
Percentile of Endowment	5.230** (1.624)	2.968 (3.966)	-8.198 (5.032)	-0.608 (4.258)	5.941 (4.092)	-0.700* (0.323)	0.572*** (0.123)
Constant	0.192 (0.215)	19.03*** (1.323)	68.28*** (1.339)	10.37*** (1.821)	91.43*** (1.153)	-0.710*** (0.100)	3.554*** (0.0270)
Observations	930	930	930	856	856	768	820
R-squared	0.619	0.100	0.111	0.131	0.174	0.285	0.224

Note: The measurement units of all the dependent variables (IQ tests) are standard deviations. T = 1 for individuals included in the treatment group; HW = 1 if the mother's expected potential wage (\hat{w}) is above the 33rd percentile of the distribution within the sample; HI = 1 if the prenatal investment index (I_0^*) is above the 33rd percentile of the distribution within the sample. All regressions include location (site) indicators. Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 4.9: Treatment effect of the IHDP intervention on inputs in the production of cognitive skills

Bibliography

- Acemoglu, D., and D. Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." *Handbook of Labor Economics* 4b:1043–1171.
- Adair, L.S., B.M. Popkin, J.S. Akin, D.K. Guilkey, S. Gultiano, J. Borja, L. Perez, C.W. Kuzawa, T. McDade, and M.J. Hindin. 2011. "Cohort Profile: the Cebu Longitudinal Health and Nutrition Survey." *International Journal of Epidemiology* 40:619–625.
- Aizer, A., and F. Cunha. 2012. "The Production of Human Capital: Endowments, Investments and Fertility." Working paper, National Bureau of Economic Research.
- Almlund, M., A.L. Duckworth, J. Heckman, and T. Kautz. 2011. "Personality Psychology and Economics." *Handbook of the Economics of Education* 4:1–181.
- Almond, D., and B. Mazumder. 2013. "Fetal Origins and Parental Responses." Working paper.
- Auger, A., and M. Burchinal. 2013. "Cognitive Stimulation and Emotional Support in Preschool Environments and Childrens Subsequent Development." Unpublished.
- Avgeropoulou, E. 2014. "The Impact of Early Childhood Conditions on Future Labor Outcomes: Does the Early-life Health and Nutritional Status affect Future Earnings into Young Adulthood? A Case Study of the Cebu Metropolitan Area, Philippines." Working paper.
- Bacol, M.M. 1971. "Inter-Generational Occupational Mobility in the Philippines." *Philippine Sociological Review* 19:193–208.
- Banerjee, A.V., and A.F. Newman. 1993. "Occupational Choice and the Process of Development." *Journal of Political Economy* 101:274–298.
- Becker, G.S. 1993. *Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education*. University of Chicago Press.
- Ben-Porath, Y. 1967. "The Production of Human Capital and the Life Cycle of Earnings." *Journal of Political Economy* 75:352–365.
- Berlin, L.J., J. Brooks-Gunn, C. McCarton, and M.C. McCormick. 1998. "The Effectiveness of Early Intervention: Examining Risk Factors and Pathways to Enhanced Development." *Preventive Medicine* 27:238–245.

- Bernal, R., and M.P. Keane. 2011. "Child Care Choices and Childrens Cognitive Achievement: The Case of Single Mothers." *Journal of Labor Economics* 29:459–512.
- . 2010. "Quasi-structural Estimation of a Model of Childcare Choices and Child Cognitive Ability Production." *Journal of Econometrics* 156:164–189.
- Blau, P.M., and O.D. Duncan. 1967. *The American Occupational Structure*. John Wiley & Sons.
- BLS. 2015. "Bureau of Labor Statistics, U.S. Department of Labor, Occupational Employment Statistics."
- Bowles, S., H. Gintis, and M. Osborne. 2001. "The Determinants of Earnings: A Behavioral Approach." *Journal of Economic Literature* 39:1137–1176.
- Bradley, R.H., L. Whiteside, D.J. Mundfrom, P.H. Casey, B.M. Caldwell, and K. Barrett. 1994. "Impact of the Infant Health and Development Program (IHDP) on the home environments of infants born prematurely and with low birthweight." *Journal of Educational Psychology* 86:531.
- Brooks-Gunn, J., P.K. Klebanov, F.r. Liaw, and D. Spiker. 1993. "Enhancing the Development of Low-Birthweight, Premature Infants: Changes in Cognition and Behavior over the First Three Years." *Child Development* 64:736–753.
- Brooks-Gunn, J., M.C. McCormick, S. Shapiro, A. Benasich, and G.W. Black. 1994. "The Effects of Early Education Intervention on Maternal Employment, Public Assistance, and Health Insurance: the Infant Health and Development Program." *American Journal of Public Health* 84:924–931.
- Budd, J.W. 2011. *The Thought of Work*. Cornell University Press.
- Bureau of Labor Statistics. 2012. *National Longitudinal Survey of Youth 1979 cohort, 1979-2012 (rounds 1-25)*. Produced and distributed by the Center for Human Resource Research, The Ohio State University, Columbus, OH, for the U.S. Department of Labor.
- Burgard, S.A. 2008. *International Encyclopedia of the Social Sciences (Occupational Status)*, W. A. Darity, ed. Macmillan.
- Cameron, A.C., and P.K. Trivedi. 2010. *Microeconometrics Using Stata*, vol. 2. Stata Press College Station, TX.
- Carba, D.B., V.L. Tan, and L.S. Adair. 2009. "Early Childhood length-for-age is Associated with the Work Status of Filipino Young Adults." *Economics and Human Biology* 7:7–17.
- Card, D. 2001. "Estimating the Return to Schooling: Progress on Some Persistent Econometric Problems." *Econometrica* 69:1127–1160.
- Carvalho, L. 2012. "Childhood Circumstances and the Intergenerational Transmission of Socioeconomic Status." *Demography* 49:913–938.

- Cascio, E.U., and D.W. Schanzenbach. 2013. "The Impacts of Expanding Access to High-Quality Preschool Education." Working paper, National Bureau of Economic Research.
- Cawley, J., J. Heckman, and E. Vytlačil. 2001. "Three Observations on Wages and Measured Cognitive Ability." *Labour Economics* 8:419–442.
- Cebu Study Team. 1992. "A Child Health Production Function Estimated from Longitudinal Data." *Journal of Development Economics* 38:323–351.
- . 1991. "Underlying and Proximate Determinants of Child Health: The Cebu Longitudinal Health and Nutrition Study." *American Journal of Epidemiology* 133:185–201.
- CEDE. 2010. "Encuesta Longitudinal sobre Dinamica de los Hogares Colombianos. Manual Integrado de Conceptos, Codificación y Captura de Datos."
- Cobb-Clark, D.A., and M. Tan. 2011. "Noncognitive Skills, Occupational Attainment, and Relative Wages." *Labour Economics* 18:1–13.
- Cunha, F., and J. Heckman. 2007. "The Technology of Skill Formation." *American Economic Review* 97:31–47.
- Cunha, F., J.J. Heckman, L. Lochner, and D.V. Masterov. 2006. "Interpreting the Evidence on Life Cycle Skill Formation." *Handbook of the Economics of Education* 1:697–812.
- Cunha, F., J.J. Heckman, and S.M. Schennach. 2010. "Estimating the Technology of Cognitive and Noncognitive Skill Formation." *Econometrica* 78:883–931.
- Del Boca, D., C. Flinn, and M. Wiswall. 2014. "Household Choices and Child Development." *The Review of Economic Studies* 81:137–185.
- Duncan, G.J., and K. Magnuson. 2013. "Investing in Preschool Programs." *The Journal of Economic Perspectives* 27:109.
- Duncan, G.J., and A.J. Sojourner. 2013. "Can intensive early childhood intervention programs eliminate income-based cognitive and achievement gaps?" *Journal of Human Resources* 48:945–968.
- Duncan, O.D. 1961. "A Socioeconomic Index for All Occupations." *Class: Critical Concepts* 1.
- Feranil, A., S. Gultiano, and L. Adair. 2008. "The Cebu Longitudinal Health and Nutrition Survey: Two Decades Later." *Asia-Pacific Population Journal* 23.
- Figlio, D., and J. Guryan. 2014. "The Effects of Poor Neonatal Health on Childrens Cognitive Development." *The American Economic Review* 104:3921–3955.
- Flood, S., M. King, S. Ruggles, and J. Warren. 2015. "Integrated public use microdata series, current population survey: Version 4.0 [Machine-readable database]." *Minneapolis: University of Minnesota*, pp. .
- Frankenberg, E., and L. Karoly. 1995. "The 1993 Indonesian Family Life Survey: Overview and Field Report." DRU-1195/1-NICHD/AID.

- Frankenberg, E., and D. Thomas. 2000. "The Indonesia Family Life Survey (IFLS): Study Design and Results from Waves 1 and 2." DRU-2238/1-NIA/NICHD.
- Fuligni, A.S., W.J. Han, and J. Brooks-Gunn. 2004. "The infant-toddler HOME in the 2nd and 3rd years of life." *Parenting* 4:139–159.
- Gelber, A., and A. Isen. 2013. "Children's Schooling and Parents' Behavior: Evidence from the Head Start Impact Study." *Journal of Public Economics* 101:25–38.
- Glewwe, P., H.G. Jacoby, and E.M. King. 2001. "Early Childhood Nutrition and Academic Achievement: a Longitudinal Analysis." *Journal of Public Economics* 81:345–368.
- Glewwe, P., and E.M. King. 2001. "The Impact of Early Childhood Nutritional Status on Cognitive Development: Does the Timing of Malnutrition Matter?" *The World Bank Economic Review* 15:81–113.
- Gormley, W.T., D. Phillips, and T. Gayer. 2008. "Preschool Programs Can Boost School Readiness." *Science* 320:1723 – 1724.
- Griliches, Z. 1977. "Estimating the Returns to Schooling: Some Econometric Problems." *Econometrica* 45:1–22.
- Gross, R.T., D. Spiker, and C.W. Haynes. 1997. *Helping low birth weight, premature babies: The Infant Health and Development Program*. Stanford University Press.
- Guthrie, G.M., A.H. Tayag, and P.J. Jacobs. 1977. "The Philippine Nonverbal Intelligence Test." *The Journal of Social Psychology* 102:3–11.
- Hanson, J.L., N. Hair, D.G. Shen, F. Shi, J.H. Gilmore, B.L. Wolfe, and S.D. Pollak. 2013. "Family poverty affects the rate of human infant brain growth." *PLoS One* 8:e80954.
- Hanushek, E., and L. Woessmann. 2008. "The Role of Cognitive Skills in Economic Development." *Journal of Economic Literature* 46:607–668.
- Hauser, R.M., and J.R. Warren. 1997. "Socioeconomic Indexes for Occupations: A Review, Update, and Critique." *Sociological Methodology* 27:177–298.
- Heckman, J. 1974. "Shadow Prices, Market Wages, and Labor Supply." *Econometrica* 42:679–694.
- Heckman, J., and B. Honore. 1990. "The Empirical Content of the Roy model." *Econometrica* 58:1121–1149.
- Heckman, J., R. LaLonde, and J. Smith. 1999. "The Economics and Econometrics of Active Labor Market Programs." *Handbook of Labor Economics* 3:1865–2097.
- Heckman, J., J. Stixrud, and S. Urzua. 2006. "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior." *Journal of Labor Economics* 24:411–482.
- Heckman, J.J. 2006. "Skill formation and the economics of investing in disadvantaged children." *Science* 312:1900–1902.

- Iglowstein, I., O.G. Jenni, L. Molinari, and R.H. Largo. 2003. "Sleep Duration from Infancy to Adolescence: Reference Values and Generational Trends." *Pediatrics* 111:302–307.
- Kimmel, J., and R. Connelly. 2007. "Mothers Time Choices Caregiving, Leisure, Home production, and Paid Work." *Journal of Human Resources* 42:643–681.
- Kisker, E., S. Hofferth, D. Phillips, and E. Farquhar. 1991. "A Profile of Child Care Settings: Early Education and Care in 1990 (Vol. 1). Princeton, NJ: Mathematica Policy Research." Working paper.
- Knudsen, E.I., J.J. Heckman, J.L. Cameron, and J.P. Shonkoff. 2006. "Economic, neurobiological, and behavioral perspectives on building Americas future workforce." *Proceedings of the National Academy of Sciences* 103:10155–10162.
- Kremer, M. 1993. "The O-Ring Theory of Economic Development." *The Quarterly Journal of Economics* 108:551–575.
- Lazear, E.P. 2009. "Firm-Specific Human Capital: A Skill-Weights Approach." *Journal of Political Economy* 117:914–940.
- Lee, N., and L.S. Adair. 2011. "Occupational and Gender Segregation and Wage Rate Differentials Among Filipino Youth." *Philippine Population Review* 6.
- Linver, M.R., A. Martin, and J. Brooks-Gunn. 2004. "Measuring Infants' Home Environment: The IT-HOME for Infants Between Birth and 12 Months in Four National Data Sets." *Parenting* 4:115–137.
- Mendez, M.A., and L.S. Adair. 1999. "Severity and Timing of Stunting in the First Two Years of Life Affect Performance on Cognitive Tests in Late Childhood." *The Journal of Nutrition* 129:1555–1562.
- Meyer, P.B., and A.M. Osborne. 2005. "Proposed category system for 1960-2000 census occupations." Working paper No. 383.
- Mincer, J. 1974. *Schooling, Experience and Earnings*. Columbia University Press.
- Morgeson, F.P., and E.C. Dierdorff. 2011. "Work Analysis: From Technique to Theory." *APA handbook of industrial and organizational psychology* 2:3–41.
- Mulligan, C.B., and Y. Rubinstein. 2008. "Selection, investment, and women's relative wages over time." *The Quarterly Journal of Economics*, pp. 1061–1110.
- Mullis, I., M. Martin, P. Foy, and A. Arora. 2012. *TIMSS 2011 International Results in Mathematics*. TIMSS & PIRLS International Study Center, Lynch School of Education, Boston College, Chestnut Hill, MA, USA.
- National Center for O*Net Development. 2016. "O*NET Database Update Summary." Unpublished, Retrieved from http://www.onetcenter.org/dl_files/Database_Update_Summary.pdf.

- National Research Council. 2010. *A Database for a Changing Economy: Review of the Occupational Information Network (O*NET)*, N. T. Tippins and M. L. Hilton, eds. The National Academies Press, Panel to Review the Occupational Information Network (O*NET).
- Neal, D.A., and W.R. Johnson. 1996. "The Role of Premarket Factors in Black-White Wage Differences." *The Journal of Political Economy* 104:869–895.
- NICHD Early Child Care Research Network. 2003. "Does Quality of Child Care Affect Child Outcomes at Age 4 1/2?" *Developmental Psychology* 39:451–469.
- Nord, C., B. Edwards, C. Andreassen, J.L. Green, and K. Wallner-Allen. 2006. "Early Childhood Longitudinal Study, Birth Cohort (ECLS-B), user's manual for the ECLS-B longitudinal 9-month–2-year data file and electronic codebook (NCES 2006–046)." *National Center for Education Statistics*, pp. .
- North, C.C., and P.K. Hatt. 1947. "Jobs and Occupations: A Popular Evaluation." *Opinion News* 9:3–13.
- OECD. 2011. *PISA 2009 Results: What Students Know and Can Do: Student Performance in Reading, Mathematics and Science.*, vol. 1. OECD Pub.
- Peet, E.D., D.C. McCoy, G. Danaei, M. Ezzati, W. Fawzi, M.R. Jarvelin, D. Pillas, and G. Fink. 2015. "Early Childhood Development and Schooling Attainment: Longitudinal Evidence from British, Finnish and Philippine Birth Cohorts." *PloS one* 10:e0137219.
- Peltzman, S. 1973. "The Effect of Government Subsidies in-kind on Private Expenditures: The Case of Higher Education." *The Journal of Political Economy*, pp. 1–27.
- Peterson, N.G., M.D. Mumford, W.C. Borman, P.R. Jeanneret, E.A. Fleishman, K.Y. Levin, M.A. Campion, M.S. Mayfield, F.P. Morgeson, K. Pearlman, et al. 2001. "Understanding work using the Occupational Information Network (O* NET): Implications for practice and research." *Personnel Psychology* 54:451–492.
- Phillips, D.A., J.P. Shonkoff, et al. 2000. *From Neurons to Neighborhoods: The Science of Early Childhood Development*. National Academies Press.
- Prada, M.F., and S.S. Urzua. 2014. "One Size Does Not Fit All: Multiple Dimensions of Ability, College Attendance and Wages." Working paper, National Bureau of Economic Research - WP20752.
- Ramey, C.T., F.A. Campbell, and S.L. Ramey. 1999. "Early intervention: Successful pathways to improving intellectual development." *Developmental Neuropsychology* 16:385–392.
- Reardon, S.F. 2011. "The widening academic achievement gap between the rich and the poor: New evidence and possible explanations." *Whither opportunity*, pp. 91–116.
- Ribar, D.C. 1995. "A Structural Model of Child Care and the Labor Supply of Married Women." *Journal of Labor Economics*, pp. 558–597.

- Rosen, S. 1986. "The Theory of Equalizing Differences." *Handbook of Labor Economics* 1:641–692.
- Rosenberg, M. 1989. *Society and the Adolescent Self-Image (Revised Edition)*. Wesleyan University Press.
- Rotter, J.B. 1966. "Generalized Expectancies for Internal versus External Control of Reinforcement." *Psychological Monographs: General and Applied* 80:1.
- Roy, A.D. 1951. "Some Thoughts on the Distribution of Earnings." *Oxford Economic Papers* 3:135–146.
- Rubalcava, L., and G. Teruel. 2007. "Guia de Usuario: Encuesta Nacional sobre Niveles de Vida de los Hogares 2002."
- Sapolsky, R.M. 2004. "Social Status and Health in Humans and other Animals." *Annual Review of Anthropology*, pp. 393–418.
- Shrout, P.E., and J.L. Fleiss. 1979. "Intraclass Correlations: Uses in Assessing Rater Reliability." *Psychological bulletin* 86:420–428.
- Spence, M. 1973. "Job Market Signaling." *The Quarterly Journal of Economics* 87:355–374.
- Strauss, J., K. Beegle, B. Sikoki, A. Dwiyanto, Y. Herawati, and F. Witoelar. 2004. "The Third Wave of the Indonesia Family Life Survey (IFLS3): Overview and Field Report." WR-144/1-NIA/NICHD.
- Strauss, J., F. Witoelar, B. Sikoki, and A. Wattie. 2009. "The Fourth Wave of the Indonesia Family Life Survey (IFLS4): Overview and Field Report." WR-675/1-NIA/NICHD.
- Tiryakian, E.A. 1959. "Occupational Satisfaction and Aspiration in an Underdeveloped Country: The Philippines." *Economic Development and Cultural Change* 7:431–444.
- . 1958. "The Prestige Evaluation of Occupations in an Under Developed Country: The Philippines." *American Journal of Sociology* 63:390–399.
- Tsacoumis, S., and S. Willison. 2010. "O*NET Analyst Occupational Skill Ratings: Procedures." Working paper No. FR-08-70, HumRRO - Human Resources Research Organization.
- U.S. Department of Labor. 2010. "The O*NET Content Model: detailed outline with descriptions." Unpublished, Document prepared by the National Center for O*Net Development. Retrieved from http://www.onetcenter.org/dl_files/ContentModel_DetailedDesc.pdf.
- Vandell, D. 2004. "Early child care: The known and the unknown." *Merrill-Palmer Quarterly* 50:387–414.
- Voth, D.E. 1970. "Occupation and Occupational Prestige in the Philippines." *Philippine Sociological Review* 18:39–64.

—. 1971. "The Problem of Occupational Prestige Rankings: Farming in the Philippines." *Rural Sociology* 36:203–210.

Wong, E.L., B.M. Popkin, D.K. Guilkey, and J.S. Akin. 1987. "Accessibility, quality of care and prenatal care use in the Philippines." *Social Science & Medicine* 24:927–944.

Appendices

A1 Job market equilibrium

There are two markets: a market for skills and a market for occupations. The distribution of skills among the labor force is represented by a cumulative distribution function $F(\mathbf{p}^1, \dots, \mathbf{p}^S) = Pr(p_i^1 \leq \mathbf{p}^1, \dots, p_i^S \leq \mathbf{p}^S)$. The distribution of occupations available in the economy is described by $G(\mathbf{r}^1, \dots, \mathbf{r}^S) = Pr(r_k^1 \leq \mathbf{r}^1, \dots, r_k^S \leq \mathbf{r}^S)$. The support of G is the set of feasible occupations, Λ .

Skills Market

Function $F(\mathbf{p}^1, \dots, \mathbf{p}^S)$ defines the supply of skills. It measures the fraction of the workforce for which vector $(\mathbf{p}^1, \dots, \mathbf{p}^S)$ represents an upper bound on their skills. The demand for skills is more complex: the worker selection problem is solved for each of the occupations on the support of function G . The solution to the worker selection problem (function P^s from Equation 2.2) indicates the optimal skill profile of the worker that should be hired to perform in each occupation. Therefore, there is a subset of occupations for which the optimal skill profile is equal to or below vector $(\mathbf{p}^1, \dots, \mathbf{p}^S)$. The demand for skills is derived from this subset of occupations, denoted by Γ .

Therefore, the equilibrium condition in the market for skills is defined as,

$$F(\mathbf{p}^1, \dots, \mathbf{p}^S) \geq \int_{\Gamma} \dots \int dG(r_k^1, \dots, r_k^S)$$

$$:$$

$$\Gamma = \left\{ (r_k^1, \dots, r_k^S) : P^s(r_k^1, \dots, r_k^S; W) \leq \mathbf{p}^s, \forall s \right\}$$

Occupations Market

The equilibrium in the market for occupations is very similar. In this case, the supply of occupations available in the economy is measured by function $G(\mathbf{r}^1, \dots, \mathbf{r}^S)$. The solution

to the occupational choice problem drives the demand for occupations (function R^s from Equation 2.4). There is a subset of individuals among the support of F who would like to work in occupations where the skill requirements are equal to or below vector $(\mathbf{r}^1, \dots, \mathbf{r}^S)$. I will denote this subset as Δ . Thus, the equilibrium condition in this market is given by,

$$G(\mathbf{r}^1, \dots, \mathbf{r}^S) \geq \int_{\Delta} \dots \int dF(p_i^1, \dots, p_i^S)$$

$$\Delta = \left\{ (p_i^1, \dots, p_i^S) : R^s(p_i^1, \dots, p_i^S; W) \leq \mathbf{r}^s, \forall s \right\}$$

Wage function, $W(p_i^1, \dots, p_i^S, r_k^1, \dots, r_k^S)$

The price mechanism of both markets is summarized in the wage function, W . Supply is inelastic in both of them, but the demand for skills and the demand for occupations respond to changes in the wage function. W and all its properties are determined as an equilibrium outcome. The wage function must be such that the equilibrium conditions are met both in the skills market and in the occupation markets. All the first-order conditions from the worker selection problem (Equation 2.1) and the occupational choice problem (Equation 2.3) must also hold.

A2 Crosswalks and merged O*NET / NLSY79 data

The NLSY79 has always classified occupations following a version of the Census Classification system. The O*Net uses a modified version of the Standard Occupational Classification (SOC) system. Occupations are defined with more detail under the SOC system, when compared to the Census system. As consequence, O*Net collects data for more than 800 occupational codes and the NLSY79 recognizes approximately 400 occupations.

- From *8-digit O*Net-SOC 2010* to *6-digit SOC 2010* (Step 1): The 2010 SOC system consists of 23 major groups, 97 minor groups, 461 broad occupations and 840 detailed occupations. It is a hierarchical system: each major group is divided into minor groups; minor groups are divided into broad occupations and broad occupations are divided into detailed occupations. The hierarchical structure is summarized in a 6-digit coding system, in which the first two digits indicate the major group, the third digit represents the minor group, the fourth and fifth digits correspond to the broad occupation and the sixth digit signals the detailed occupation. For example, trailer truck drivers (53-3032) is a detailed occupation contained inside a broad occupation called "Driver/Sales Workers and Truck Drivers" (53-3030), which is part of a minor group called "Motor Vehicle Operators" (53-3000). This minor group belongs to a major group called "Transportation and Material Moving Occupations" (53-0000).

The classification system used by O*Net is heavily based on the SOC system. It uses an 8-digit code. The first 6 digits correspond to the equivalent 6-digit SOC 2010 detailed occupation. The seventh and eighth digit are used in case a more refined definition of the occupation is needed, specially in the case of new or rapidly growing occupations. As an example, baristas have a stand-alone occupation in O*Net (35-3022.01), but they are not a detailed occupation under the SOC. The corresponding SOC detailed occupation is "Counter Attendants, Cafeteria, Food Concession, and Coffee Shop" (35-3022). As another example, the SOC detailed occupation of "Clinical, Counseling, and School Psychologists" (19-3031) is broken down in O*Net into three separate occupations: school psychologists (19-3031.01), clinical psychologists (19-3031.02) and counseling psychologists (19-3031.03). If no refinement is needed, then the seventh and eighth digits are equal to "00".

In most cases, there is a one-to-one correspondence between an 8-digit O*Net SOC code and a 6-digit SOC 2010 detailed occupation. In the other cases, when the last two digits are different than "00", then the equivalent O*Net score for the 6-digit SOC detailed occupation is equal to the average score among those 8-digit occupations which share their first six digits.

- From *6-digit SOC 2010* to *6-digit SOC 2000* (Step 2): The Bureau of Labor Statistics published a crosswalk between the 2010 SOC and the 2000 SOC on February 2010. The crosswalk is publicly available (<http://www.bls.gov/soc/soccrosswalks.htm>). There is a one-to-one correspondence between most detailed occupations from both systems. However, in some cases, a 2000 SOC detailed occupation was divided into two or more titles in the 2010 classification. If so, then the O*Net score for the 2000 SOC occu-

		O*Net importance scores (1 to 5 scale)		
		Knowledge Math	Knowledge Language	Work Styles Persistence
Occupation (6-digit SOC)	Employment			
Electrical Engineers (172071)	441,390	4.25	3.92	4.38
Electronics Engineers (172072)	395,800	4.06	3.67	3.85
Employment-weighted average, all occ.		2.91	3.39	3.71
Employment-weighted std. deviation, all occ.		0.62	0.60	0.45
		O*Net standardized scores (Z scores)		
Occupation (6-digit SOC)	Weights			
Electrical Engineers (172071)	0.53	2.17	0.88	1.48
Electronics Engineers (172072)	0.47	1.86	0.46	0.32
		Aggregated O*Net scores (Z scores)		
Occupation (4-digit Census)				
Electrical and Electronics Engineers (1410)		2.20	0.69	0.93

Note: calculations based on the SOC-Census crosswalk created by [Acemoglu and Autor \(2011\)](#).

Table A1: From 6-digit SOC 2000 to 4-digit Census 2000: the case of Electrical and Electronic Engineers.

pation corresponds to the average score of its related 2010 SOC titles. For example, Registered Nurses are coded as 29-1111 under the 2000 SOC. This title was divided into four detailed occupations in the 2010 SOC system: stand-alone Registered Nurses (29-1141), Nurse Anesthetists (29-1151), Nurse Midwives (29-1161) and Nurse Practitioners (29-1171).

- From *6-digit SOC 2000* to *4-digit Census 2000* (Step 3): Each SOC occupational code corresponds to only one Census code, but most Census codes are related to more than one SOC code. 4-digit Census codes can be interpreted as consolidations of 6-digit SOC codes. Thus, O*Net scores must be aggregated somehow. [Acemoglu and Autor \(2011\)](#) faced the same problem and proposed a solution based on data from the Occupational Employment Statistics (OES). I used the SOC-Census crosswalk created by Acemoglu and Autor.

The OES reports total employment by occupation in the United States at the 6-digit SOC level and is included in the SOC-Census crosswalk by Acemoglu and Autor. Their key idea is to use total employment as weights. Therefore, the O*Net score of a 4-digit Census occupation is equal to the employment-weighted average O*Net score of the corresponding 6-digit SOC occupations. Additionally, I standardized all O*Net scores using employment-weighted averages and standard deviations. Table [A1](#) presents as an example the case of Electrical and Electronic Engineers (4-digit 2000 Census code 1410).

- From *4-digit Census 2000* to *4-digit Census 1990* (Step 4): the Minnesota Population

Center (MPC) has a rich set of crosswalks for the different Census classifications systems published during the second half of the twentieth century. The crosswalks are publicly available at <https://usa.ipums.org/usa/volii/> and are explained by [Meyer and Osborne \(2005\)](#). There is a MPC crosswalk that links 4-digit Census 2000 codes with the equivalent 4-digit Census 1990 codes. Furthermore, the crosswalk includes total employment for each occupation in the 1990 classification system. The availability of employment data allowed me to implement Acemoglu and Autor's methodology. That is, in those cases where a 4-digit 1990 code corresponds to more than one 4-digit 2000 code, I use total employment to generate a new weighted average O*Net score.

- From *4-digit Census 1990* to *3-digit Census 1970* (Step 5) and *3-digit Census 1980* (Step 6): The MPC crosswalk explained by [Meyer and Osborne \(2005\)](#) summarizes the links between the 1990 Census codes and other Census classifications from other decades. In particular, each 3-digit code in the 1970 Census system corresponds to one 4-digit 1990 Census code. A similar property holds for the 1980 classification system. Therefore, the last step assigns to each 1970 / 1980 Census code the O*Net score computed for the corresponding 1990 Census occupation. This last step is critical, due to the Census codes historically used by the NLSY79: the 1970 system was used between 1979 and 1993; the 1980 system was used between 1982 and 2000, and the 2000 has been used since 2002.

A3 First stage regressions - Relative Skills

Table A2: First Stage - Relative Math Skills ($p_i^M - \bar{p}_{k,\epsilon}^M$)

	1992	2000	2010
Female indicator	-0.172*** (0.014)	-0.145*** (0.015)	-0.173*** (0.016)
African American indicator	-0.020 (0.018)	-0.007 (0.019)	-0.014 (0.021)
Hispanic indicator	-0.037** (0.019)	-0.067*** (0.020)	-0.070*** (0.023)
Mother's Occupation in 1978: Math O*Net score	-0.022** (0.010)	-0.022** (0.011)	-0.004 (0.012)
Father's Occupation in 1978: Math O*Net score	-0.007 (0.009)	-0.018** (0.009)	-0.018* (0.010)
Mother's Occupation in 1978: Language O*Net score	0.010 (0.011)	0.003 (0.012)	-0.003 (0.013)
Father's Occupation in 1978: Language O*Net score	-0.022** (0.010)	-0.008 (0.010)	-0.016 (0.011)
Rotter Locus of Control, 1979 (Z Score)	0.005 (0.007)	0.005 (0.008)	0.006 (0.008)
Rosenberg Self-Esteem, 1980 (Z Score)	-0.014* (0.007)	-0.002 (0.008)	0.003 (0.009)
* Occupational Aspiration in 1982: Math O*Net score (r_z^M)	0.136*** (0.008)	0.134*** (0.008)	0.158*** (0.009)
* Occupational Aspiration in 1982: Language O*Net score (r_z^L)	0.181*** (0.009)	0.156*** (0.009)	0.175*** (0.010)
* Relative Math Skills, Occ. Aspiration in 1982 ($p_i^M - \bar{p}_{z,\epsilon}^M$)	0.857*** (0.012)	0.851*** (0.012)	0.867*** (0.013)
* Relative Language Skills, Occ. Aspiration in 1982 ($p_i^L - \bar{p}_{z,\epsilon}^L$)	-0.037*** (0.012)	-0.063*** (0.013)	-0.051*** (0.014)
Constant	-0.072 (0.123)	-0.059 (0.166)	-0.026 (0.233)
R^2	0.79	0.77	0.79
F statistic	2377.473	2079.967	1846.293
Observations	3796	3549	2883

Heteroskedasticity-robust s.e in parentheses. Instrumental variables are preceded by an asterisk (*).

Additional controls: age and missing value indicators for parent's occ. in 1978. $\epsilon = 0.25$

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: First Stage - Relative Language Skills ($p_i^L - \bar{p}_{k,\epsilon}^L$)

	1992	2000	2010
Female indicator	-0.193*** (0.014)	-0.172*** (0.015)	-0.185*** (0.016)
African American indicator	-0.031* (0.018)	-0.020 (0.019)	-0.030 (0.021)
Hispanic indicator	-0.051*** (0.019)	-0.078*** (0.020)	-0.071*** (0.022)
Mother's Occupation in 1978: Math O*Net score	-0.016 (0.010)	-0.016 (0.011)	-0.002 (0.012)
Father's Occupation in 1978: Math O*Net score	-0.008 (0.008)	-0.016* (0.009)	-0.016 (0.010)
Mother's Occupation in 1978: Language O*Net score	0.005 (0.011)	-0.003 (0.012)	-0.009 (0.013)
Father's Occupation in 1978: Language O*Net score	-0.019** (0.009)	-0.004 (0.010)	-0.011 (0.011)
Rotter Locus of Control, 1979 (Z Score)	0.005 (0.007)	0.009 (0.008)	0.005 (0.008)
Rosenberg Self-Esteem, 1980 (Z Score)	-0.010 (0.007)	-0.006 (0.008)	0.001 (0.009)
* Occupational Aspiration in 1982: Math O*Net score (r_z^M)	0.074*** (0.008)	0.067*** (0.008)	0.091*** (0.009)
* Occupational Aspiration in 1982: Language O*Net score (r_z^L)	0.216*** (0.009)	0.193*** (0.010)	0.209*** (0.011)
* Relative Math Skills, Occ. Aspiration in 1982 ($p_i^M - \bar{p}_{z,\epsilon}^M$)	-0.120*** (0.011)	-0.118*** (0.012)	-0.105*** (0.013)
* Relative Language Skills, Occ. Aspiration in 1982 ($p_i^L - \bar{p}_{z,\epsilon}^L$)	0.939*** (0.011)	0.903*** (0.012)	0.917*** (0.014)
Constant	-0.042 (0.125)	-0.109 (0.166)	-0.162 (0.229)
R^2	0.81	0.78	0.79
F statistic	2677.328	2098.894	1646.161
Observations	3796	3549	2883

Heteroskedasticity-robust s.e in parentheses. Instrumental variables are preceded by an asterisk (*).

Additional controls: age and missing value indicators for parent's occ. in 1978. $\epsilon = 0.25$

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A4 Regression tables from 1992 to 2012

Table A4: OLS models - Ln of Hourly Rate of Pay

	1992	1994	1996	1998	2000	2002	2004	2006	2008	2010	2012
Age (years)	0.015*** (0.004)	0.007 (0.005)	-0.002 (0.005)	-0.001 (0.005)	-0.002 (0.005)	-0.004 (0.006)	0.001 (0.006)	0.001 (0.006)	-0.006 (0.006)	0.003 (0.006)	-0.012* (0.006)
Female indicator	-0.189*** (0.015)	-0.202*** (0.017)	-0.202*** (0.017)	-0.238*** (0.017)	-0.254*** (0.018)	-0.276*** (0.020)	-0.288*** (0.020)	-0.296*** (0.021)	-0.287*** (0.020)	-0.275*** (0.021)	-0.290*** (0.022)
African American indicator	-0.097*** (0.020)	-0.068*** (0.021)	-0.055*** (0.021)	-0.041** (0.021)	-0.071*** (0.022)	-0.017 (0.024)	-0.023 (0.026)	-0.025 (0.026)	0.016 (0.024)	-0.011 (0.026)	-0.014 (0.027)
Hispanic indicator	0.032 (0.021)	0.049** (0.023)	0.046** (0.023)	0.027 (0.023)	0.021 (0.023)	0.011 (0.027)	0.048* (0.026)	0.028 (0.028)	0.048* (0.026)	0.034 (0.027)	0.068** (0.028)
Mother's Occupation in 1978: Math O*Net score	0.013 (0.011)	0.001 (0.012)	0.009 (0.013)	0.030** (0.013)	0.025* (0.014)	-0.003 (0.015)	0.006 (0.015)	0.001 (0.016)	-0.003 (0.014)	0.018 (0.015)	0.009 (0.016)
Father's Occupation in 1978: Math O*Net score	0.017** (0.009)	0.018* (0.010)	0.020** (0.010)	0.012 (0.011)	0.015 (0.011)	0.024* (0.012)	0.023* (0.013)	0.016 (0.013)	0.031** (0.012)	0.016 (0.013)	0.013 (0.013)
Mother's Occupation in 1978: Language O*Net score	0.021* (0.013)	0.034** (0.013)	0.047*** (0.015)	0.015 (0.014)	0.020 (0.015)	0.035** (0.016)	0.036** (0.016)	0.037** (0.016)	0.043*** (0.016)	0.034** (0.016)	0.053*** (0.017)
Father's Occupation in 1978: Language O*Net score	0.010 (0.010)	0.012 (0.012)	0.005 (0.011)	-0.000 (0.011)	0.019 (0.012)	0.008 (0.014)	0.011 (0.014)	0.030** (0.014)	-0.007 (0.014)	0.008 (0.014)	0.020 (0.014)
Mother's Occupation in 1978: Missing ind.	-0.032** (0.015)	-0.006 (0.017)	-0.020 (0.017)	-0.025 (0.017)	-0.026 (0.018)	-0.012 (0.020)	-0.043** (0.020)	-0.035* (0.021)	-0.003 (0.020)	-0.011 (0.020)	-0.030 (0.021)
Father's Occupation in 1978: Missing ind.	-0.045** (0.018)	-0.023 (0.019)	-0.055** (0.019)	-0.027 (0.019)	-0.043** (0.020)	-0.043** (0.022)	-0.040* (0.022)	-0.078** (0.023)	-0.046** (0.021)	-0.015 (0.022)	-0.059** (0.024)
Rotter Locus of Control, 1979 (Z Score)	0.021*** (0.008)	0.028*** (0.008)	0.020** (0.009)	0.018** (0.008)	0.030*** (0.009)	0.029*** (0.010)	0.035*** (0.011)	0.035*** (0.010)	0.025** (0.010)	0.023** (0.011)	0.026** (0.011)
Rosenberg Self-Esteem, 1980 (Z Score)	0.068*** (0.008)	0.058*** (0.009)	0.069*** (0.009)	0.067*** (0.009)	0.065*** (0.010)	0.070*** (0.010)	0.053*** (0.011)	0.063*** (0.012)	0.067*** (0.011)	0.060*** (0.011)	0.048*** (0.011)
→ Relative Math Skills, Current Occ. ($p_k^M - \bar{p}_{k,\epsilon}^M$)	0.080*** (0.012)	0.097*** (0.014)	0.104*** (0.014)	0.117*** (0.014)	0.106*** (0.015)	0.090*** (0.016)	0.137*** (0.017)	0.136*** (0.017)	0.137*** (0.016)	0.128*** (0.016)	0.149*** (0.017)
→ Relative Language Skills, Current Occ. ($p_k^L - \bar{p}_{k,\epsilon}^L$)	0.026*** (0.013)	0.023 (0.014)	0.028*** (0.014)	0.024* (0.014)	0.036** (0.015)	0.045*** (0.016)	0.008 (0.018)	0.008 (0.018)	0.015 (0.017)	0.028 (0.018)	0.016 (0.018)
→ Current Occupation: Math O*Net score (r_k^M)	0.069*** (0.008)	0.069*** (0.009)	0.074** (0.009)	0.083** (0.009)	0.103*** (0.010)	0.083** (0.010)	0.070** (0.011)	0.081*** (0.011)	0.077*** (0.011)	0.096** (0.011)	0.085*** (0.012)
→ Current Occupation: Language O*Net score (r_k^L)	0.121*** (0.008)	0.138*** (0.010)	0.144*** (0.010)	0.147*** (0.009)	0.137*** (0.010)	0.173*** (0.011)	0.187*** (0.011)	0.178*** (0.012)	0.182*** (0.011)	0.172*** (0.011)	0.172*** (0.012)
Constant	1.928*** (0.134)	2.216*** (0.162)	2.610*** (0.167)	2.662*** (0.180)	2.823*** (0.198)	2.971*** (0.231)	2.850*** (0.246)	2.907*** (0.268)	3.264*** (0.267)	2.880*** (0.289)	3.674*** (0.318)
R^2	0.25	0.23	0.25	0.27	0.29	0.27	0.29	0.28	0.28	0.27	0.28
Average age (years)	29.9	31.9	33.8	35.7	37.9	39.8	42.1	43.7	45.6	47.5	50.3
Observations	3796	3669	3828	3690	3549	3151	2881	2880	2949	2883	2727

Heteroskedasticity-robust standard errors in parentheses. $\epsilon = 0.25$
 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: IV models - Ln of Hourly Rate of Pay

	1992	1994	1996	1998	2000	2002	2004	2006	2008	2010	2012
Age (years)	0.018*** (0.005)	0.014* (0.006)	0.003 (0.006)	0.002 (0.006)	0.010 (0.007)	0.019* (0.011)	0.017* (0.009)	0.013 (0.010)	0.009 (0.011)	0.012 (0.009)	-0.004 (0.009)
Female indicator	-0.202*** (0.037)	-0.217*** (0.051)	-0.198*** (0.046)	-0.256*** (0.044)	-0.289*** (0.066)	-0.296*** (0.064)	-0.332*** (0.063)	-0.410*** (0.085)	-0.361*** (0.090)	-0.420*** (0.076)	-0.345*** (0.078)
African American indicator	-0.051** (0.025)	0.037 (0.039)	0.040 (0.033)	0.034 (0.034)	0.025 (0.039)	0.100** (0.050)	0.073* (0.044)	0.112** (0.056)	0.129** (0.051)	0.062 (0.045)	0.065 (0.042)
Hispanic indicator	0.035 (0.026)	0.068* (0.037)	0.070** (0.035)	0.059* (0.034)	0.027 (0.039)	-0.023 (0.050)	0.025 (0.043)	0.042 (0.050)	0.034 (0.053)	-0.009 (0.045)	0.086* (0.044)
Mother's Occupation in 1978: Math O*Net score	-0.003 (0.014)	-0.003 (0.017)	0.006 (0.016)	0.018 (0.016)	0.009 (0.018)	-0.026 (0.025)	-0.002 (0.021)	-0.002 (0.024)	0.006 (0.025)	0.022 (0.022)	0.005 (0.020)
Father's Occupation in 1978: Math O*Net score	0.007 (0.011)	-0.013 (0.016)	0.003 (0.013)	-0.009 (0.014)	-0.009 (0.015)	-0.041 (0.028)	-0.005 (0.019)	-0.013 (0.022)	-0.031 (0.027)	-0.026 (0.021)	-0.014 (0.018)
Mother's Occupation in 1978: Language O*Net score	0.017 (0.014)	0.013 (0.020)	0.040** (0.020)	0.018 (0.018)	0.003 (0.021)	0.001 (0.026)	0.003 (0.023)	-0.023 (0.030)	0.002 (0.029)	-0.009 (0.025)	0.032 (0.023)
Father's Occupation in 1978: Language O*Net score	0.002 (0.013)	-0.009 (0.017)	-0.015 (0.014)	-0.014 (0.014)	-0.001 (0.016)	-0.000 (0.022)	-0.004 (0.020)	0.010 (0.023)	-0.042 (0.026)	-0.022 (0.022)	-0.001 (0.020)
Mother's Occupation in 1978: Missing ind.	-0.019 (0.018)	0.014 (0.023)	-0.017 (0.021)	-0.007 (0.021)	0.002 (0.023)	0.081** (0.040)	0.022 (0.031)	0.040 (0.039)	0.063 (0.039)	0.037 (0.031)	0.017 (0.031)
Father's Occupation in 1978: Missing ind.	-0.009 (0.023)	0.013 (0.029)	-0.012 (0.026)	-0.004 (0.024)	-0.001 (0.027)	0.004 (0.038)	0.019 (0.033)	-0.019 (0.040)	0.048 (0.044)	0.047 (0.036)	-0.025 (0.032)
Rotter Locus of Control, 1979 (Z Score)	0.016* (0.009)	0.013 (0.012)	0.015 (0.011)	0.013 (0.010)	0.013 (0.012)	-0.004 (0.018)	0.022 (0.015)	0.032* (0.016)	0.017 (0.018)	0.009 (0.016)	0.014 (0.015)
Rosenberg Self-Esteem, 1980 (Z Score)	0.044*** (0.011)	0.028** (0.014)	0.038*** (0.013)	0.038*** (0.012)	0.022 (0.015)	0.028 (0.019)	0.029* (0.015)	0.023 (0.021)	0.028 (0.021)	0.030* (0.017)	0.022 (0.016)
→ Relative Math Skills, Current Occ. ($p_k^M - \bar{p}_{k,\epsilon}^M$)	0.043* (0.025)	0.006 (0.041)	0.035 (0.031)	0.059** (0.027)	0.019 (0.038)	-0.048 (0.054)	0.054 (0.035)	0.007 (0.057)	0.011 (0.050)	0.030 (0.040)	0.099*** (0.033)
→ Relative Language Skills, Current Occ. ($p_k^L - \bar{p}_{k,\epsilon}^L$)	0.029* (0.017)	0.032 (0.024)	0.049** (0.022)	0.047 (0.022)	0.047 (0.029)	0.060* (0.032)	0.003 (0.032)	0.018 (0.036)	0.005 (0.036)	-0.001 (0.031)	0.002 (0.031)
→ Current Occupation: Math O*Net score (r_k^M)	0.327*** (0.076)	0.516*** (0.135)	0.453*** (0.111)	0.388*** (0.087)	0.481*** (0.136)	0.723*** (0.200)	0.517*** (0.136)	0.611*** (0.196)	0.743*** (0.207)	0.494*** (0.153)	0.487*** (0.128)
→ Current Occupation: Language O*Net score (r_k^L)	0.158*** (0.060)	0.224*** (0.082)	0.189*** (0.074)	0.238*** (0.066)	0.259*** (0.096)	0.297*** (0.089)	0.340*** (0.091)	0.413*** (0.124)	0.340*** (0.121)	0.426*** (0.105)	0.259*** (0.101)
Constant	1.775*** (0.161)	1.921*** (0.242)	2.319*** (0.222)	2.465*** (0.230)	2.294*** (0.292)	1.986*** (0.467)	2.129*** (0.386)	2.357*** (0.449)	2.495*** (0.504)	2.435*** (0.434)	3.239*** (0.427)
Average age (years)	29.9	31.9	33.8	35.7	37.9	39.8	42.1	43.7	45.6	47.5	50.3
Durbin-Wu-Hausman (DWH) test	24.716	24.478	27.655	37.099	53.380	32.877	33.152	21.591	26.744	19.656	27.404
DWH p-value	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
Observations	3796	3669	3828	3690	3549	3151	2881	2880	2949	2883	2727

Heteroskedasticity-robust standard errors in parentheses. $\epsilon = 0.25$
 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: First Stage - Current Occupation O*Net Score: Math (r_k^M)

	1992	1994	1996	1998	2000	2002	2004	2006	2008	2010	2012
Age (years)	-0.009 (0.010)	-0.011 (0.010)	-0.010 (0.010)	-0.006 (0.010)	-0.019* (0.010)	-0.032*** (0.010)	-0.027** (0.011)	-0.013 (0.011)	-0.018 (0.011)	-0.014 (0.011)	-0.011 (0.012)
Female indicator	-0.024 (0.032)	-0.072** (0.032)	-0.078** (0.032)	-0.107*** (0.032)	-0.105*** (0.033)	-0.084*** (0.034)	-0.094*** (0.036)	-0.062* (0.036)	-0.056 (0.036)	-0.050 (0.036)	-0.014 (0.037)
African American indicator	-0.092** (0.042)	-0.183*** (0.043)	-0.187*** (0.041)	-0.193*** (0.042)	-0.170*** (0.044)	-0.150*** (0.045)	-0.166*** (0.048)	-0.211*** (0.047)	-0.147*** (0.046)	-0.159*** (0.046)	-0.146*** (0.048)
Hispanic indicator	0.024 (0.043)	-0.054 (0.044)	-0.054 (0.043)	-0.121*** (0.044)	-0.038 (0.045)	0.018 (0.048)	0.004 (0.051)	-0.079 (0.051)	-0.020 (0.050)	0.005 (0.050)	-0.044 (0.051)
Mother's Occupation in 1978: Math O*Net score	0.058** (0.023)	0.009 (0.024)	0.016 (0.024)	0.046* (0.024)	0.044* (0.024)	0.032 (0.026)	0.010 (0.027)	0.005 (0.027)	-0.012 (0.027)	-0.026 (0.027)	0.006 (0.028)
Father's Occupation in 1978: Math O*Net score	0.027 (0.020)	0.053*** (0.020)	0.032 (0.020)	0.049** (0.020)	0.047** (0.020)	0.092*** (0.022)	0.052** (0.024)	0.043* (0.023)	0.078*** (0.022)	0.075*** (0.023)	0.055** (0.024)
Mother's Occupation in 1978: Language O*Net score	-0.011 (0.025)	0.014 (0.026)	-0.015 (0.026)	-0.055** (0.026)	-0.009 (0.027)	0.024 (0.028)	0.027 (0.030)	0.057** (0.029)	0.027 (0.029)	0.049 (0.030)	0.013 (0.030)
Father's Occupation in 1978: Language O*Net score	0.021 (0.022)	0.021 (0.021)	0.033 (0.022)	0.016 (0.021)	0.012 (0.022)	-0.014 (0.022)	-0.006 (0.025)	-0.009 (0.024)	0.017 (0.023)	-0.004 (0.024)	0.018 (0.026)
Mother's Occupation in 1978: Missing ind.	-0.026 (0.032)	-0.028 (0.032)	0.009 (0.032)	-0.033 (0.032)	-0.038 (0.033)	-0.108*** (0.035)	-0.086** (0.037)	-0.081** (0.037)	-0.052 (0.036)	-0.034 (0.037)	-0.059 (0.038)
Father's Occupation in 1978: Missing ind.	-0.088** (0.037)	-0.042 (0.037)	-0.075** (0.037)	-0.010 (0.037)	-0.051 (0.038)	-0.024 (0.039)	-0.061 (0.041)	-0.034 (0.041)	-0.092** (0.040)	-0.066 (0.041)	-0.040 (0.042)
Rotter Locus of Control, 1979 (Z Score)	-0.001 (0.017)	0.021 (0.017)	0.001 (0.017)	-0.002 (0.017)	0.027 (0.017)	0.038** (0.018)	0.010 (0.019)	-0.002 (0.019)	0.006 (0.019)	0.013 (0.019)	0.012 (0.021)
Rosenberg Self-Esteem, 1980 (Z Score)	0.047*** (0.017)	0.028 (0.017)	0.040** (0.017)	0.030* (0.018)	0.044** (0.018)	0.035* (0.018)	0.014 (0.019)	0.030 (0.020)	0.030 (0.019)	0.021 (0.019)	0.022 (0.020)
* Relative Math, Occ. Aspiration in 1982 ($p_i^M - \bar{p}_{z,\epsilon}^M$)	0.162*** (0.027)	0.183*** (0.028)	0.186*** (0.027)	0.167*** (0.027)	0.211*** (0.027)	0.171*** (0.028)	0.147*** (0.030)	0.170*** (0.029)	0.134*** (0.029)	0.127*** (0.030)	0.115*** (0.032)
* Relative Language, Occ. Aspiration in 1982 ($p_i^L - \bar{p}_{z,\epsilon}^L$)	0.016 (0.027)	-0.024 (0.027)	-0.038 (0.026)	0.024 (0.026)	-0.025 (0.027)	-0.023 (0.029)	-0.012 (0.030)	-0.049 (0.030)	0.001 (0.029)	0.009 (0.029)	0.040 (0.031)
* Occ. Aspiration in 1982: Math O*Net score (r_z^M)	0.152*** (0.018)	0.126*** (0.018)	0.133*** (0.018)	0.152*** (0.018)	0.129*** (0.018)	0.114*** (0.019)	0.135*** (0.021)	0.115*** (0.021)	0.113*** (0.020)	0.129*** (0.020)	0.144*** (0.022)
* Occ. Aspiration in 1982: Language O*Net score (r_z^L)	0.058*** (0.020)	0.056*** (0.020)	0.085*** (0.020)	0.107*** (0.020)	0.096*** (0.021)	0.043** (0.021)	0.069*** (0.022)	0.029 (0.023)	0.055*** (0.023)	0.054*** (0.023)	0.082*** (0.024)
Constant	0.310 (0.291)	0.493 (0.322)	0.512 (0.328)	0.426 (0.353)	0.928*** (0.383)	1.355*** (0.417)	1.191** (0.464)	0.701 (0.488)	0.892* (0.496)	0.716 (0.528)	0.599 (0.582)
R^2	0.08	0.08	0.08	0.10	0.10	0.08	0.08	0.07	0.07	0.07	0.07
F statistic	37.419	29.345	33.582	43.407	38.764	21.698	20.578	17.378	17.388	18.082	20.430
Observations	3796	3669	3828	3690	3549	3151	2881	2880	2949	2883	2727

Heteroskedasticity-robust standard errors in parentheses. $\epsilon = 0.25$
 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: First Stage - Current Occupation O*Net Score: Language (r_k^L)

	1992	1994	1996	1998	2000	2002	2004	2006	2008	2010	2012
Age (years)	-0.018** (0.009)	-0.008 (0.009)	-0.009 (0.008)	0.001 (0.009)	-0.015* (0.009)	-0.005 (0.010)	-0.013 (0.010)	-0.011 (0.010)	-0.011 (0.010)	-0.006 (0.010)	-0.016 (0.010)
Female indicator	0.420*** (0.030)	0.416*** (0.029)	0.387*** (0.029)	0.397*** (0.030)	0.462*** (0.030)	0.447*** (0.033)	0.435*** (0.034)	0.519*** (0.034)	0.542*** (0.034)	0.532*** (0.034)	0.582*** (0.036)
African American indicator	0.060 (0.038)	0.014 (0.040)	-0.004 (0.036)	0.089** (0.039)	0.032 (0.039)	0.004 (0.042)	0.006 (0.044)	-0.013 (0.044)	-0.011 (0.044)	0.008 (0.043)	0.048 (0.045)
Hispanic indicator	0.118*** (0.039)	0.180*** (0.039)	0.175*** (0.039)	0.171*** (0.040)	0.189*** (0.039)	0.207*** (0.044)	0.195*** (0.047)	0.149*** (0.046)	0.171*** (0.047)	0.164*** (0.045)	0.152*** (0.048)
Mother's Occupation in 1978: Math O*Net score	0.049** (0.022)	0.005 (0.022)	-0.028 (0.022)	0.001 (0.023)	0.008 (0.022)	0.030 (0.024)	0.025 (0.025)	0.009 (0.025)	0.017 (0.024)	0.033 (0.025)	0.036 (0.026)
Father's Occupation in 1978: Math O*Net score	0.011 (0.018)	0.032* (0.018)	0.025 (0.018)	0.036** (0.018)	0.029 (0.018)	0.026 (0.020)	0.016 (0.022)	0.012 (0.022)	0.038* (0.021)	0.037* (0.022)	0.022 (0.023)
Mother's Occupation in 1978: Language O*Net score	0.023 (0.024)	0.078*** (0.024)	0.111*** (0.024)	0.067*** (0.025)	0.077*** (0.024)	0.056** (0.026)	0.062** (0.027)	0.076*** (0.027)	0.065** (0.027)	0.052* (0.027)	0.064** (0.027)
Father's Occupation in 1978: Language O*Net score	0.063*** (0.020)	0.070*** (0.020)	0.037* (0.019)	0.024 (0.020)	0.052*** (0.020)	0.069*** (0.022)	0.060** (0.023)	0.070*** (0.023)	0.097*** (0.022)	0.084*** (0.022)	0.071*** (0.024)
Mother's Occupation in 1978: Missing ind.	-0.034 (0.029)	-0.024 (0.029)	-0.013 (0.029)	-0.029 (0.029)	-0.047 (0.030)	-0.115*** (0.033)	-0.114*** (0.034)	-0.102*** (0.033)	-0.133*** (0.034)	-0.112*** (0.034)	-0.146*** (0.035)
Father's Occupation in 1978: Missing ind.	-0.122*** (0.034)	-0.101*** (0.033)	-0.084** (0.033)	-0.072** (0.034)	-0.048 (0.034)	-0.115*** (0.037)	-0.098** (0.039)	-0.112*** (0.038)	-0.116*** (0.037)	-0.094** (0.037)	-0.077* (0.039)
Rotter Locus of Control, 1979 (Z Score)	0.013 (0.015)	0.014 (0.015)	0.024 (0.015)	0.008 (0.015)	-0.003 (0.015)	0.021 (0.015)	0.021 (0.018)	0.005 (0.018)	0.016 (0.018)	0.022 (0.018)	0.021 (0.019)
Rosenberg Self-Esteem, 1980 (Z Score)	0.057*** (0.016)	0.056*** (0.015)	0.062*** (0.015)	0.070*** (0.016)	0.078*** (0.016)	0.061*** (0.018)	0.038*** (0.019)	0.053*** (0.018)	0.050*** (0.018)	0.041** (0.018)	0.056*** (0.019)
* Relative Math, Occ. Aspiration in 1982 ($p_i^M - \bar{p}_{z,\epsilon}^M$)	0.150*** (0.024)	0.144*** (0.025)	0.124*** (0.025)	0.142*** (0.025)	0.121*** (0.025)	0.146*** (0.027)	0.116*** (0.029)	0.143*** (0.028)	0.134*** (0.028)	0.155*** (0.028)	0.131*** (0.030)
* Relative Language, Occ. Aspiration in 1982 ($p_i^L - \bar{p}_{z,\epsilon}^L$)	0.111*** (0.023)	0.123*** (0.025)	0.123*** (0.023)	0.158*** (0.024)	0.160*** (0.025)	0.137*** (0.028)	0.160*** (0.029)	0.119*** (0.029)	0.135*** (0.029)	0.124*** (0.028)	0.156*** (0.029)
* Occ. Aspiration in 1982: Math O*Net score (r_z^M)	0.035** (0.016)	0.024 (0.016)	0.038** (0.015)	0.035** (0.016)	0.051*** (0.016)	0.026 (0.017)	0.032* (0.018)	0.025 (0.018)	0.017 (0.018)	0.038** (0.018)	0.047** (0.019)
* Occ. Aspiration in 1982: Language O*Net score (r_z^L)	0.247*** (0.019)	0.241*** (0.019)	0.259*** (0.019)	0.285*** (0.019)	0.244*** (0.019)	0.291*** (0.021)	0.273*** (0.022)	0.228*** (0.021)	0.246*** (0.022)	0.249*** (0.022)	0.261*** (0.023)
Constant	0.214 (0.271)	-0.058 (0.284)	-0.007 (0.286)	-0.400 (0.319)	0.266 (0.337)	-0.072 (0.389)	0.255 (0.432)	0.180 (0.432)	0.244 (0.466)	0.030 (0.486)	0.504 (0.530)
R^2	0.21	0.21	0.21	0.22	0.23	0.24	0.22	0.23	0.24	0.24	0.25
F statistic	81.522	80.114	85.673	110.487	89.676	91.696	71.637	59.247	64.797	74.012	68.488
Observations	3796	3669	3828	3690	3549	3151	2881	2880	2949	2883	2727

Heteroskedasticity-robust standard errors in parentheses. $\epsilon = 0.25$
 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: First Stage - Relative Math Skills ($p_i^M - \bar{p}_{k,\epsilon}^M$)

	1992	1994	1996	1998	2000	2002	2004	2006	2008	2010	2012
Age (years)	0.001 (0.004)	-0.001 (0.004)	-0.002 (0.004)	-0.003 (0.004)	0.002 (0.004)	0.002 (0.005)	0.007 (0.005)	0.008* (0.005)	0.003 (0.005)	0.001 (0.005)	0.004 (0.005)
Female indicator	-0.172*** (0.014)	-0.157*** (0.014)	-0.139*** (0.014)	-0.145*** (0.014)	-0.145*** (0.015)	-0.143*** (0.015)	-0.154*** (0.015)	-0.170*** (0.015)	-0.180*** (0.015)	-0.173*** (0.016)	-0.190*** (0.016)
African American indicator	-0.020 (0.018)	0.025 (0.019)	0.010 (0.018)	-0.020 (0.019)	-0.007 (0.019)	-0.028 (0.020)	-0.011 (0.021)	0.004 (0.021)	-0.010 (0.020)	-0.014 (0.021)	-0.040* (0.022)
Hispanic indicator	-0.037** (0.019)	-0.048** (0.020)	-0.063** (0.020)	-0.050** (0.020)	-0.067*** (0.020)	-0.086*** (0.022)	-0.066*** (0.022)	-0.042* (0.022)	-0.068*** (0.022)	-0.070*** (0.023)	-0.064*** (0.023)
Mother's Occupation in 1978: Math O*Net score	-0.022** (0.010)	-0.006 (0.010)	-0.016 (0.010)	-0.017* (0.010)	-0.022** (0.011)	-0.014 (0.011)	-0.010 (0.012)	-0.007 (0.011)	0.007 (0.011)	-0.004 (0.012)	-0.015 (0.012)
Father's Occupation in 1978: Math O*Net score	-0.007 (0.009)	-0.020** (0.009)	-0.009 (0.009)	-0.016* (0.009)	-0.018** (0.009)	-0.014 (0.010)	-0.017* (0.010)	-0.011 (0.010)	-0.018* (0.011)	-0.018* (0.010)	-0.021** (0.011)
Mother's Occupation in 1978: Language O*Net score	0.010 (0.011)	-0.004 (0.011)	0.009 (0.011)	0.021* (0.012)	0.003 (0.012)	-0.004 (0.012)	0.005 (0.013)	-0.005 (0.013)	-0.015 (0.012)	-0.003 (0.013)	-0.010 (0.013)
Father's Occupation in 1978: Language O*Net score	-0.022** (0.010)	-0.014 (0.010)	-0.011 (0.010)	-0.002 (0.010)	-0.008 (0.010)	-0.019* (0.011)	-0.009 (0.011)	-0.012 (0.011)	-0.011 (0.011)	-0.016 (0.011)	-0.005 (0.012)
Mother's Occupation in 1978: Missing ind.	-0.004 (0.014)	-0.017 (0.014)	-0.017 (0.014)	-0.013 (0.014)	-0.002 (0.015)	0.021 (0.016)	0.011 (0.016)	0.015 (0.016)	0.027* (0.016)	0.009 (0.016)	0.021 (0.017)
Father's Occupation in 1978: Missing ind.	0.051*** (0.015)	0.018 (0.016)	0.026* (0.016)	0.008 (0.016)	0.032* (0.017)	0.051*** (0.017)	0.043** (0.018)	0.044** (0.017)	0.038** (0.017)	0.040** (0.018)	0.021 (0.019)
Rotter Locus of Control, 1979 (Z Score)	0.005 (0.007)	0.003 (0.007)	0.009 (0.007)	0.009 (0.007)	0.005 (0.008)	-0.008 (0.008)	-0.005 (0.008)	0.007 (0.008)	0.010 (0.008)	0.006 (0.008)	0.004 (0.009)
Rosenberg Self-Esteem, 1980 (Z Score)	-0.014* (0.007)	-0.014* (0.008)	-0.010 (0.008)	-0.001 (0.008)	-0.002 (0.008)	0.008 (0.008)	0.018** (0.009)	0.006 (0.009)	0.002 (0.008)	0.003 (0.009)	0.001 (0.009)
* Relative Math, Occ. Aspiration in 1982 ($p_i^M - \bar{p}_{z,\epsilon}^M$)	0.857*** (0.012)	0.849*** (0.012)	0.853*** (0.012)	0.853*** (0.012)	0.851*** (0.012)	0.864*** (0.014)	0.886*** (0.014)	0.888*** (0.013)	0.881*** (0.013)	0.867*** (0.013)	0.873*** (0.014)
* Relative Language, Occ. Aspiration in 1982 ($p_i^L - \bar{p}_{z,\epsilon}^L$)	-0.037*** (0.012)	-0.041*** (0.012)	-0.047*** (0.012)	-0.064*** (0.012)	-0.063*** (0.013)	-0.053*** (0.014)	-0.058*** (0.014)	-0.048*** (0.014)	-0.049*** (0.013)	-0.051*** (0.014)	-0.065*** (0.014)
* Occ. Aspiration in 1982: Math O*Net score (r_z^M)	0.136*** (0.008)	0.150*** (0.008)	0.142*** (0.008)	0.136*** (0.008)	0.134*** (0.008)	0.155*** (0.008)	0.148*** (0.009)	0.156*** (0.009)	0.166*** (0.009)	0.158*** (0.009)	0.153*** (0.010)
* Occ. Aspiration in 1982: Language O*Net score (r_z^L)	0.181*** (0.009)	0.168*** (0.009)	0.170*** (0.009)	0.158*** (0.009)	0.156*** (0.009)	0.166*** (0.010)	0.170*** (0.010)	0.186*** (0.010)	0.177*** (0.010)	0.175*** (0.010)	0.174*** (0.011)
Constant	-0.072 (0.123)	-0.015 (0.138)	0.031 (0.139)	0.116 (0.151)	-0.059 (0.166)	-0.083 (0.181)	-0.274 (0.193)	-0.351* (0.203)	-0.158 (0.216)	-0.026 (0.233)	-0.188 (0.254)
R^2	0.79	0.78	0.78	0.78	0.77	0.79	0.80	0.81	0.81	0.79	0.79
F statistic	2377.473	2216.455	2227.365	2041.345	2079.967	1848.667	1669.772	1908.449	1918.648	1846.293	1599.216
Observations	3796	3669	3828	3690	3549	3151	2881	2880	2949	2883	2727

Heteroskedasticity-robust standard errors in parentheses. $\epsilon = 0.25$
 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9: First Stage - Relative Language Skills ($p_i^L - \bar{p}_{k,\epsilon}^L$)

	1992	1994	1996	1998	2000	2002	2004	2006	2008	2010	2012
Age (years)	0.002 (0.004)	-0.000 (0.004)	0.000 (0.004)	-0.000 (0.004)	0.004 (0.004)	0.003 (0.005)	0.008 (0.005)	0.010** (0.005)	0.006 (0.005)	0.004 (0.005)	0.007 (0.005)
Female indicator	-0.193*** (0.014)	-0.185*** (0.014)	-0.174*** (0.014)	-0.173*** (0.014)	-0.172*** (0.015)	-0.173*** (0.015)	-0.168*** (0.016)	-0.192*** (0.016)	-0.203*** (0.015)	-0.185*** (0.016)	-0.207*** (0.017)
African American indicator	-0.031* (0.018)	0.009 (0.019)	0.001 (0.018)	-0.036* (0.019)	-0.020 (0.019)	-0.053*** (0.020)	-0.028 (0.021)	-0.017 (0.021)	-0.027 (0.021)	-0.030 (0.021)	-0.058*** (0.022)
Hispanic indicator	-0.051*** (0.019)	-0.060*** (0.020)	-0.074*** (0.019)	-0.065*** (0.020)	-0.078*** (0.020)	-0.094*** (0.022)	-0.075*** (0.022)	-0.059*** (0.022)	-0.078*** (0.022)	-0.071*** (0.022)	-0.074*** (0.023)
Mother's Occupation in 1978: Math O*Net score	-0.016 (0.010)	-0.005 (0.010)	-0.010 (0.010)	-0.010 (0.010)	-0.016 (0.011)	-0.011 (0.011)	-0.004 (0.012)	-0.004 (0.012)	0.008 (0.011)	-0.002 (0.012)	-0.008 (0.013)
Father's Occupation in 1978: Math O*Net score	-0.008 (0.008)	-0.015* (0.009)	-0.010 (0.009)	-0.014 (0.009)	-0.016* (0.009)	-0.011 (0.010)	-0.012 (0.010)	-0.011 (0.010)	-0.017* (0.011)	-0.016 (0.010)	-0.019* (0.011)
Mother's Occupation in 1978: Language O*Net score	0.005 (0.011)	-0.006 (0.011)	-0.001 (0.011)	0.014 (0.012)	-0.003 (0.012)	-0.010 (0.013)	-0.003 (0.013)	-0.012 (0.013)	-0.021 (0.013)	-0.009 (0.013)	-0.019 (0.013)
Father's Occupation in 1978: Language O*Net score	-0.019** (0.009)	-0.015 (0.010)	-0.009 (0.009)	0.001 (0.010)	-0.004 (0.010)	-0.015 (0.011)	-0.006 (0.011)	-0.006 (0.011)	-0.009 (0.011)	-0.011 (0.011)	-0.001 (0.012)
Mother's Occupation in 1978: Missing ind.	-0.005 (0.014)	-0.014 (0.014)	-0.020 (0.014)	-0.018 (0.014)	-0.007 (0.015)	0.015 (0.016)	0.004 (0.016)	0.006 (0.016)	0.021 (0.016)	0.002 (0.016)	0.009 (0.017)
Father's Occupation in 1978: Missing ind.	0.047*** (0.015)	0.017 (0.016)	0.022 (0.015)	0.010 (0.016)	0.032* (0.017)	0.050*** (0.018)	0.034* (0.018)	0.035* (0.018)	0.028 (0.018)	0.031* (0.018)	0.019 (0.019)
Rotter Locus of Control, 1979 (Z Score)	0.005 (0.007)	0.006 (0.007)	0.014** (0.007)	0.010 (0.007)	0.009 (0.008)	-0.002 (0.008)	-0.002 (0.008)	0.008 (0.008)	0.008 (0.008)	0.005 (0.008)	0.003 (0.009)
Rosenberg Self-Esteem, 1980 (Z Score)	-0.010 (0.007)	-0.011 (0.008)	-0.009 (0.007)	-0.005 (0.008)	-0.006 (0.008)	0.004 (0.009)	0.014 (0.009)	0.003 (0.009)	-0.000 (0.009)	0.001 (0.009)	-0.004 (0.009)
* Relative Math, Occ. Aspiration in 1982 ($p_i^M - \bar{p}_{z,\epsilon}^M$)	-0.120*** (0.011)	-0.124*** (0.012)	-0.112*** (0.012)	-0.122*** (0.012)	-0.118*** (0.012)	-0.108*** (0.013)	-0.088*** (0.014)	-0.094*** (0.013)	-0.097*** (0.013)	-0.105*** (0.013)	-0.108*** (0.014)
* Relative Language, Occ. Aspiration in 1982 ($p_i^L - \bar{p}_{z,\epsilon}^L$)	0.939*** (0.011)	0.929*** (0.011)	0.919*** (0.012)	0.908*** (0.012)	0.903*** (0.012)	0.910*** (0.014)	0.906*** (0.015)	0.918*** (0.014)	0.917*** (0.013)	0.917*** (0.014)	0.906*** (0.015)
* Occ. Aspiration in 1982: Math O*Net score (r_z^M)	0.074*** (0.008)	0.083*** (0.008)	0.081*** (0.007)	0.070*** (0.008)	0.067*** (0.008)	0.087*** (0.008)	0.082*** (0.009)	0.091*** (0.009)	0.098*** (0.008)	0.091*** (0.009)	0.086*** (0.010)
* Occ. Aspiration in 1982: Language O*Net score (r_z^L)	0.216*** (0.009)	0.205*** (0.009)	0.206*** (0.009)	0.195*** (0.009)	0.193*** (0.010)	0.192*** (0.010)	0.196*** (0.010)	0.215*** (0.010)	0.205*** (0.011)	0.209*** (0.011)	0.205*** (0.011)
Constant	-0.042 (0.125)	0.014 (0.138)	0.004 (0.139)	0.068 (0.152)	-0.109 (0.166)	-0.076 (0.182)	-0.261 (0.198)	-0.392* (0.209)	-0.226 (0.219)	-0.162 (0.229)	-0.310 (0.258)
R^2	0.81	0.80	0.80	0.79	0.78	0.79	0.80	0.80	0.80	0.79	0.78
F statistic	2677.328	2498.310	2544.644	2235.576	2098.894	1787.860	1594.098	1594.044	1800.130	1646.161	1485.856
Observations	3796	3669	3828	3690	3549	3151	2881	2880	2949	2883	2727

Heteroskedasticity-robust standard errors in parentheses. $\epsilon = 0.25$
 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A5 Other longitudinal studies

Indonesia Family Life Survey - IFLS

The IFLS started in 1993. The main goal of this longitudinal survey was to explore the determinants and consequences of health status in Indonesia (Frankenberg and Karoly, 1995). To carry out this goal, the research team collected data for a nationally representative random sample of 7,440 households. A novel approach of this study was to use direct and objective measures of health conditions, like blood pressure or tests on blood samples. The study also pioneered the collection of data beyond the household. Extensive community questionnaires were used to gather information about health facilities, schooling infrastructure and food prices. New data was collected again in the following rounds:

- 1997/8, known as IFLS2 (Frankenberg and Thomas, 2000).
- 2000, known as IFLS3 (Strauss et al., 2004).
- 2007/8, known as IFLS4 (Strauss et al., 2009).

A summary of the most relevant properties of the IFLS can be found in Table A10.²⁰ The IFLS has collected measures of cognitive skills from children, adolescents and young adults since the second round of the study (1997/8). According to the survey’s documentation, the instrument used during the second round was very long and created a heavy burden on many respondents (Strauss et al., 2009, Vol. 2, pp. 46-47). Therefore, the instrument was simplified for the third and fourth rounds. Since 2000, general cognitive level is measured using a short version of Raven’s progressive matrices test, which is only 12-questions long. Numeracy skills are tested using five progressive math problems, organized by their difficulty. Two versions of both instruments are used: one for children age 7 to 14 and another one for adolescents and young adults who are between 15 and 24.

Unfortunately, the IFLS has no questions about occupational aspirations, similar to those found in the NLSY79 and in the CLHNS data. It does collect detailed information on current and previous occupations for all members in the household. Occupations were recorded *verbatim* and then coded in-house using 98 occupational codes at a 2-digit level, based on the “Standard ITC” system (Strauss et al., 2009, Vol. 1, p. 33).

Mexican Family Life Survey - MxFLS

The MxFLS has the same purposes and methodological approach as the IFLS (Rubalcava and Teruel, 2007). All relevant information about the Mexican survey is available in Table A11. The project leader is a former Mexican graduate student at UCLA (Graciela Teruel), who gained the necessary field experience working on the Indonesian survey. For

²⁰Publicly available data from all four waves of the IFLS can be found at <http://www.rand.org/labor/FLS/IFLS.html>

	1993/4 IFLS1	1997/8 IFLS2	2000 IFLS3	2007/8 IFLS4
Proficiency Scores General Cog. Skills		Raven's progres- sive matrices test (long)	Raven's test (short)	Raven's test (short)
Math, Numeracy		Long test	Short test	Short test
Ages		***	7-14 (EK1), 15-24 (EK2)	7-14 (EK1), 15-24 (EK2)
Occupational Codes	"Standard ITC" (2-digits)	Same as IFLS1	Same as IFLS1	Same as IFLS1
Number of Codes	98 Occupational codes	Same as IFLS1	Same as IFLS1	Same as IFLS1
1) Occ. aspiration	-	-	-	-
2) Parents' occupation	Yes	Yes	Yes	Yes

Table A10: Summary of the **IFLS** (Indonesia)

this reason, the scientific committees behind both surveys have several members in common and there are many similarities between them: the Indonesian household and community questionnaires were adapted to the Mexican context and objective measures of health conditions were also collected. Baseline data was collected in 2002, when a random sample of 8,440 households from all across Mexico were selected. There have been two follow-up rounds since then. The first follow-up happened in 2005/6 and the third follow-up went to the field in 2009/10. Only data from the baseline and the first follow-up are publicly available.²¹

One advantage of the MxFLS is that general cognitive skills are measured in people of many different ages. Respondents who were between 5 and 12 years old solved a Raven's test with a total of 18 questions, whereas respondents between 13 and 65 years of age solved a more difficult Raven's test composed of 12 questions (Rubalcava and Teruel, 2007, p. 15). The same tests have been used in every round. There are no measures of specific language or math skills in the MxFLS.

The work module in the survey collects information about current and past occupations for every member of the household, but there is no question that inquires about occupational aspirations for the future. As in the IFLS, the respondent could provide an open-ended occupation that was latter coded in-house by the research team. In this case, the Mexican Occupational Classifications system (CMO) was used (Rubalcava and Teruel, 2007, p. 36). The CMO follows a hierarchical system, based on the digits of every code. The CMO has 19 main groups at the 2-digit level; 137 subgroups at the 3-digit level and 465 4-digit unitary groups. Unfortunately, the research team coded all occupations using only the 19 2-digit categories.²²

²¹MxFLS data is available at <http://www.ennvih-mxfls.org/>.

²²I contacted technical support for the MxFLS and asked them if there is any information available based on the 3-digit or 4-digit CMO codes. They told me that is not the case.

	2002 MxFLS-1	2005/6 MxFLS-2	2009/10 MxIFLS-3
Proficiency Scores General Cog. Skills	Raven's test (short)	Raven's test (short)	***
Ages	5-12 (Module EN), 13-65 (Module EA)	Same as MxFLS-1	
Occupational Codes	Mexican occupa- tional classification system (CMO, 2-digits)	Same as MxFLS-1	***
Number of Codes	19 codes	19 codes	***
1) Occ. aspiration	-	-	***
2) Parents' occupation	Yes	Yes	***

Table A11: Summary of the **MxFLS** (Mexico)

Colombian Longitudinal Survey of Wealth, Income, Labor and Land - ELCA

One final longitudinal study I considered is the ELCA from Colombia (CEDE, 2010).²³ This is a long-term study that started recently and it is the initiative of the Department of Economics at *Universidad de los Andes*. Their goal is to follow a random sample of 10,800 households from all around the country for at least 10 years. The first round of data was collected in 2010. The second round of data was collected during the first semester of 2013 and therefore is not yet publicly available. A language skill test (the Peabody Picture Vocabulary test in Spanish) has been given to children between 3 and 9 years old. The employment section of the household questionnaire uses very broad occupational categories (8 in total) and there are no questions about occupational aspirations for the future.

In conclusion, the current design and data availability of the ELCA would not allow me to implement the econometric strategy. However, the results from my dissertation, based on data from the United States and the Philippines, might allow me to create an academic interaction with the research team behind this Colombian study and suggest them specific adjustments to future rounds of the survey, to include questions about occupational aspirations and use a detailed occupational classification system.

²³For more information about the ELCA available at <http://encuestalongitudinal.uniandes.edu.co/index.php/en>.

A6 Instructions given to Filipino respondents

How to fill out the required education column [column D]?

Consider the minimum level of education which a worker must have, **in the Province of Cebu of The Philippines**, to be hired for the occupation you are analyzing.

Each level of education has an identification code. Please write the code in the corresponding cell.

<i>Code</i>	<i>Level of education</i>
10	None
20	Elementary (Primary)
30	Some Secondary (Incomplete)
40	Complete Secondary (High School degree)
50	Training or vocational degree
55	Some college (Incomplete)
60	Undergraduate degree
70	Post-graduate degree

How to fill out reading, writing, speaking and math skills columns [columns E,F,G and H]?

These questions are about work-related skills. A skill is the ability to perform a task well. It is usually developed over time through training or experience.

Consider the importance of each skill for the proper performance of each occupation **in the Province of Cebu of The Philippines**. The definition of each skill is the following:

- **Reading Skills [Column E]:** “Understand written sentences and paragraphs in work–related documents”.
- **Writing Skills [Column F]:** “Communicating effectively in writing as appropriate for the needs of the audience”.
- **Speaking Skills [Column G]:** “Talking to others to convey information effectively”.
- **Math skills [Column H]:** “Using mathematics to solve problems”.

Please rate all skills for each occupation using the following 5-point scale:

<i>Code</i>	<i>Importance</i>
1	Not important
2	Somewhat important
3	Important
4	Very important
5	Extremely important

If you do not recognize the name of the occupation in English, please take a couple of minutes to find the translation to your native language on the Internet.

Salamat!

[Adapted from the ONet Skills Questionnaire - US Department of Labor]

A7 Kuhn-Tucker conditions for the post-natal parental problem

$$\frac{\partial \mathcal{L}}{\partial \lambda} = w [T_p - T_c] + wt + Y - c - [\pi q^n - w] n - wl = 0; \lambda \geq 0 \quad (\text{A1})$$

$$\frac{\partial \mathcal{L}}{\partial \mu} = \bar{\tau} - t \geq 0; \frac{\partial \mathcal{L}}{\partial \mu} \mu = 0; \mu \geq 0 \quad (\text{A2})$$

$$\frac{\partial \mathcal{L}}{\partial c} = U_c - \lambda \leq 0; \frac{\partial \mathcal{L}}{\partial c} c = 0; c \geq 0 \quad (\text{A3})$$

$$\frac{\partial \mathcal{L}}{\partial q^n} = U_h f_1 n - \lambda \pi n \leq 0; \frac{\partial \mathcal{L}}{\partial q^n} q^n = 0; q^n \geq 0 \quad (\text{A4})$$

$$\frac{\partial \mathcal{L}}{\partial e} = U_p r + U_h f_2 q_e^r \leq 0; \frac{\partial \mathcal{L}}{\partial e} e = 0; e \geq 0 \quad (\text{A5})$$

$$\frac{\partial \mathcal{L}}{\partial n} = U_h [f_1 q^n - f_2 q^r] - U_p e - \lambda [\pi q^n - w] \leq 0; \frac{\partial \mathcal{L}}{\partial n} n = 0; n \geq 0 \quad (\text{A6})$$

$$\frac{\partial \mathcal{L}}{\partial l} = U_l - \lambda w \leq 0; \frac{\partial \mathcal{L}}{\partial l} l = 0; l \geq 0 \quad (\text{A7})$$

$$\frac{\partial \mathcal{L}}{\partial t} = U_h [f_1 q^t - f_2 q^r] + U_t - U_p e + \lambda w - \mu \leq 0; \frac{\partial \mathcal{L}}{\partial t} [t - \bar{\tau}] = 0; 0 \leq t \leq \bar{\tau} \quad (\text{A8})$$

A8 Measurement of quality of non-maternal care (q^n)

Quality of nonmaternal care

The IHDP data has very specific information about non-maternal care. The survey asked for the primary and secondary caregivers during a typical week at the 18-month, 24-month, 30-month and 36-month family interviews. The respondent could choose from nine different categories (partner, sibling, grandmother, another relative, babysitter, day care home, day care center, someone else and the child’s father, if he lives in another home). However, the IHDP did not directly measure the quality of non-maternal care.

To get a continuous measure the quality of these care settings, we draw in data from a pioneering study of nonmaternal care quality, the Study of Early Child Care and Youth Development (SECCYD) by the National Institute of Child Health and Human Development (NICHD). The SECCYD collected panel data on child and family characteristics and their use of various care settings. The SECCYD classifies non-maternal caregivers into nine categories: father / partner, grandparent in-home, grandparent out-of-home, other relative in-home, other relative out-of-home, non-relative in-home, non-relative out-of-home, child care center and others. The study included a sample of 1,364 children aged 0 to 3 during 1991 to 1994 in 10 study sites around the country, 2 of which overlap with the IHDP’s 8 sites.²⁴

For each child and each nonmaternal care setting used, the SECCYD measured care quality using the Observational Record of the Childcare Environment (ORCE) (NICHD Early Child Care Research Network, 2003; Vandell, 2004), which is composed of three different types of scores: Behavioral Scales, Qualitative Ratings and measures of Structural Variables. We follow Auger and Burchinal (2013), who suggest that a good measure of the quality of interactions geared toward cognitive stimulus is the ORCE’s Qualitative Rating on Stimulation of Development. This rating is available in the SECCYD data at 15, 24 and 36 months (Phase 1).

We estimate a pooled OLS model in the SECCYD data, in which the dependent variable is standardized ORCE Qualitative Rating on Stimulation of Development. The set of predictors must be variables available in both the SECCYD and IHDP datasets. They include child’s age, birth order, gender, birth weight (level and square), gestational age at birth (level and square), maternal age at child birth, maternal education (four categories), race, ethnicity, marital status, and study site. As a predictor, we also use the standardized Learning and Literacy score based on components from the HOME score (Fuligni, Han, and Brooks-Gunn, 2004). Finally, we match the nine categories of non-maternal caregivers from the IHDP with the nine categories used in the SECCYD. Thus, the last set of predictors is indicators for the category of the caregiver.

²⁴The 10 sites of the SECCYD – NICHD study are University of Arkansas, UC Irvine, University of Kansas, University of New Hampshire, Penn State University, Temple University, University of Virginia, University of Washington, Western Carolina Center and University of Wisconsin. The sites which overlap with the IHDP study are the University of Arkansas and the University of Washington.

After estimating the linear relationship between mean nonmaternal care quality and the set of predictors in the SECCYD, we score each IHDP child based on the same set of predictors and impute that mean prediction as the IHDP child’s measure of nonmaternal-care quality (\tilde{q}^n). Summary statistics for the SECCYD data and model estimates are displayed in Appendix Tables A12 and A13, respectively.

To pin down the price of nonmaternal care (π) and the scale of our nonmaternal care quality measure (q^n), we calibrate to data on average hourly child care prices from a conveniently-timed, nationally-representative survey of home- and center-based providers carried out during 1989-1990 (Kisker et al., 1991). We normalize the location of q^n to match the average quality of center-based care in the SECCYD: $q^n_{center} \equiv \tilde{q}^n_{center} = 3.62$.

Next, we calibrate π using price data. The average price of an hour of center-based care for children 12-36 months of age was \$2.82 (2012\$). In our model, the hourly price of care is $p(q^n) = \pi q^n$. This implies $\pi = \$0.7796 = \$2.82/3.62$.

By combining data on the differences in price and quality between home-based and center-based care, we calibrate q^n to have a meaningful scale. Our model implies that two care settings with quality difference Δq^n will have hourly price difference $\Delta p = \pi \Delta q^n$.²⁵ Therefore, the average observed quality of home-based care should obey:

$$q^n_{home} = q^n_{center} + \frac{\Delta p}{\pi} \tag{A9}$$

The observed difference in average hourly price between home-based care and center-based care is $\Delta p = \$0.09$ (Kisker et al., 1991). The equation above implies that $q^n_{home} = 3.74$ and, so, this implies that $\Delta q^n = 3.74 - 3.62 = 0.12$. In the original quality metric, $\Delta \tilde{q}^n = 0.58$. The ratio of these quality differences is 0.207. Therefore, to convert from an arbitrary quality scale to a scale grounded in observed price differences, we set $q^n \equiv 0.207(\tilde{q}^n - 3.62)$.

In order to calculate the heterogeneous treatment effects on the quality of non-maternal care, we standardize q^n within the IHDP sample.

²⁵Kisker et al. (1991) provides substantial evidence that, consistent with our model, hourly prices rise in quality. For instance, settings with lower child-teacher ratios and a higher share of teachers with a college degree charge higher average prices.

A9 Supplementary Tables and Figures - Chapter 4

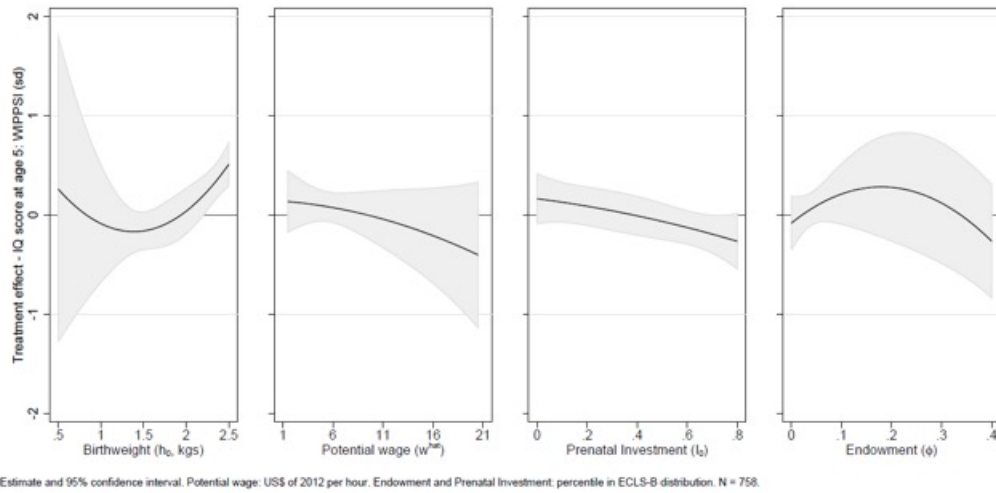


Figure A1: Heterogeneity in treatment effects on Age 8 IQ

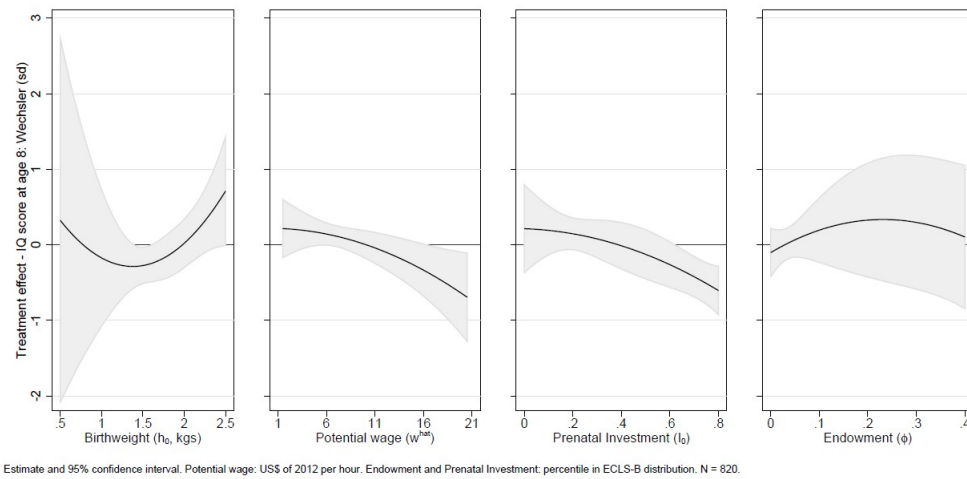


Figure A2: Heterogeneity in treatment effects on Age 8 IQ

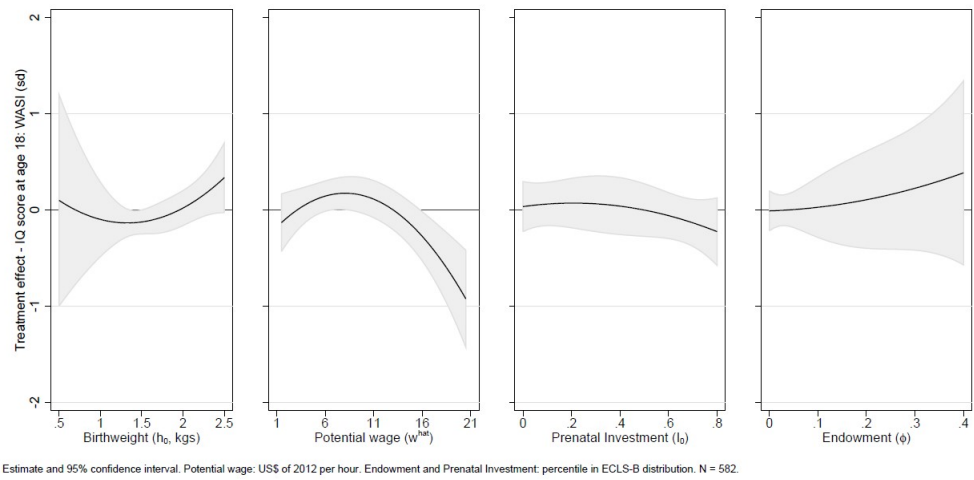


Figure A3: Heterogeneity in treatment effects on Age 18 IQ

	Mean	Std. Dev.	Min	Max	N
ORCE, Stimulation of Development score	0.00	1.00	-1.39	3.26	1,837
Child's age (months)	25.29	8.64	15	36	1,837
Birth order	1.67	0.81	1	5	1,837
Female indicator	0.49	0.50	0	1	1,837
Child's birth weight (kgs)	3.50	0.51	2	5.34	1,837
Child's gestational age (weeks)	39.27	1.47	33	43	1,837
Mother's age (years)	28.92	5.39	18	46	1,837
Learning and Literacy Score, HOME Inventory	5.02	0.89	0	6.13	1,837
Mother's Education	Percent				
Less than High School	4.9				
High School graduate	17.8				
Some College	35.0				
College graduate	42.4				
Race and Ethnicity	Percent				
Non-Hispanic White	82.6				
African American	10.3				
Hispanic	4.3				
Other	2.7				
Non-Maternal Caregiver	Percent				
Father / Partner	14.8				
Grandparent	10.3				
Another Relative	5.6				
Non-Relative In-Home	10.8				
Day Care Home	27.3				
Child Care Center	31.3				

Table A12: Descriptive statistics from the NICHD – SECCYD data

Child's age indicator, 24 months	0.0305 (0.0463)
Child's age indicator, 36 months	0.0940* (0.0500)
Child's birth order	-0.125*** (0.0348)
Female child indicator	0.123** (0.0536)
Birth weight (grams)	0.412 (0.472)
Birth weight squared	-0.0571 (0.0661)
Child's gestational age	0.884* (0.511)
Child's gestational age squared	-0.0114* (0.00663)
Mother's age	0.0106* (0.00625)
Mother's education: Less than High School	0.0228 (0.126)
Mother's education: Some college	0.0943 (0.0722)
Mother's education: College graduate	0.150* (0.0802)
Race and ethnicity: African-American	-0.194** (0.0861)
Race and ethnicity: Hispanic	-0.104 (0.143)
Race and ethnicity: Other	0.179 (0.128)
Marital status: Single	-0.132 (0.0916)
Marital status: Separated / Divorced / Widowed	-0.260 (0.179)
Avg. Learning and Literacy score, 15m and 36m	0.142*** (0.0339)
Non-Maternal Caregiver: Father / Partner	0.336*** (0.0889)

Table A13: Model estimates for the quality of non-maternal care in the SECCYD – NICHD data

Non-Maternal Caregiver: Grandparent	0.342*** (0.0949)
Non-Maternal Caregiver: Another Relative	0.0302 (0.104)
Non-Maternal Caregiver: Non-Relative In-Home	0.534*** (0.105)
Non-Maternal Caregiver: Day Care Home	0.138** (0.0661)
Constant	-18.94** (9.626)
Observations	1,837
R-squared	0.140

Note: the dependent variable is the Observational Rating of the Caregiving Environment (ORCE), Stimulation of Development score. The excluded child's age category is 15 months. The excluded mother's education category is high school graduates. The excluded race and ethnicity category are non-Hispanic whites. The excluded marital status category is married women. The excluded non-maternal caregiver category is child care centers. 9 site dummies are included but not reported.

Table A13: Model estimates for the quality of non-maternal care in the SECCYD – NICHD data (continued...)

VARIABLES	(1) HOME Total Score at 12 Months	(2) Bayley Mental Index- Corrected Age
Treatment indicator = 1	-0.0636 (0.187)	0.180 (0.106)
Potential wage above 33th percentile = 1	0.642*** (0.172)	0.210** (0.0863)
Treatment x Pot. Wage \geq 33th perc.	0.0673 (0.0905)	-0.222 (0.144)
Prenatal Invest. above 33th perc. (in sample) = 1	0.262*** (0.0702)	0.208** (0.0877)
Treatment x Prenatal Invest. \geq 33th perc.	0.0516 (0.215)	-0.00242 (0.153)
Percentile of Endowment	-1.418** (0.484)	0.715** (0.288)
Constant	-0.507*** (0.117)	0.196* (0.0852)
Observations	828	846
R-squared	0.195	0.142

Robust standard errors in parentheses
*** p_i0.01, ** p_i0.05, * p_i0.1

Table A14: Treatment effect at 12 months on HOME score and Bayley test